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Data-driven selection of greenhouse gas mitigation measures in the plastics industry

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ABSTRACT

The complexity of corporate decarbonisation strategies and a shortage of specialists in the field of energy consultants necessitate the development of data-based simulation tools. In this study, an ecological-economic simulation model is presented, which can be used to reduce information deficits and develop company-specific decarbonisation strategies. It uses the next-event time progression method. Data considered include those from a processed version of the publicly available Industrial Assessment Center database. Based on different cost and emission development forecasts, a decarbonisation strategy is developed with sector-specific filtering of the data and various other parameters. The Python-based simulation model calculates costs, savings, and investment times of measures within the framework of a decarbonisation strategy. The model is applied in a case study. The comparison of modelled and manually developed strategies shows a 2.1 % difference in total greenhouse gas emissions. 4 of the 13 identified measures in the simulation model are comparable with measures from the manually developed strategy. The similarity of the savings achieved as well as the overlap of measures indicate a successful applicability for industry companies. Furthermore, the identification of alternative measures can help consultants to develop decarbonization strategies. A decarbonization strategy can be devised for any company with minimal data such as industry type, energy requirements, and annual turnover. More detailed information allows more precise calculations, but industry averages are stored for all key values within the sector to ensure a tailored strategy can be developed with little data. With the model, each company of an implemented sector can receive a starting point for developing their own decarbonisation strategy.

1. Introduction

With increasing temperatures, rising sea levels, and more frequent extreme weather events, the need to mitigate and adapt to the impacts of climate change is becoming increasingly urgent. A survey commissioned by the European Union in 2021 shows that 49 % of Europeans identify climate change and environmental concerns are the leading global challenges for the future (European Union, 2021). In response, governments, businesses, and other stakeholders worldwide have set ambitious climate targets to reduce greenhouse gas emissions (GHGE) and limit global warming to 2 °C above pre-industrial levels, as outlined in the Paris Agreement (United Nations, 2015). However, achieving these targets will require a significant transformation of the economy. Driven by social, political, and economic imperatives, companies find themselves under increasing pressure to plan and implement decarbonisation strategies. Corporate decarbonisation strategies are an essential part of achieving climate targets. The development of a decarbonisation strategy requires time, information, and knowledge. However, to achieve net zero GHGE by 2050, companies need to reduce emissions as fast as possible (European Comission, 2023). A reduction can be achieved through measures in efficiency (energy and materials), consistency (substitution of fossil energy sources and materials), and the sequestration of GHGE. Sustainable decarbonisation strategies are primarily not aimed at offsetting but at avoiding and reducing GHGE (Huckestein, 2020). The reduction of emissions is not limited to the direct processes of a respective company. Ebersold et al. (2023) investigated how carbon insetting can be used to mitigate GHGE in industrial supply chains. Cadez et al. (2019) examined different climate strategies for similarities. They concluded that companies focus more on individual strategies, and similarities are rare. Hechelmann et al. (2023b) conducted a technical and economical comparison of decarbonisation

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Nomenclature

AC	Abatement cost
ARC	Assessment Recommendation Code
CCF	Corporate Carbon Footprint
DF	Data frame
EF	Emission factor
GHG	Greenhouse Gas
GHGE	Greenhouse Gas Emissions
IAC	Industrial Assessment Center
kWh	Kilowatt-hour
SBTi	Science Based Targets initiative

strategies for manufacturing. They concluded that the abatement potential and feasibility of strategies depend on individual preconditions. A survey of over 2500 German companies revealed that the development of a corporate decarbonisation strategy is hindered by obstacles and uncertainties (DIHK, 2021). Automation and digitisation represent a solution to compensate for the lack of qualified specialists in order to achieve the national climate protection targets together with industry (BMBF, 2023).

Guminski et al. (2017) examined current reduction measures in the industry to identify and quantify the technical potential for corporate decarbonisation strategies. Graichen et al. (2021) and Strandberg-Salmon et al. (2020) focused on implementing climate strategies into existing management systems and activities. Additionally, the development of general and sector-specific decarbonisation strategies has been researched by Day et al. (2022). Their results showed that existing strategies lack transparency and ambition. Hübner et al. (2021) and Miller et al. (2021) focused on specific industries, while Hannen (2020) and Lieback et al. (2021) developed cross-sectoral guidelines prioritizing GHGE avoidance and reduction over compensation. Drechsler et al. (Drechsler et al., 2017) and Kreibich et al. (Kreibich et al., 2021) provided specific recommendations for developing a corporate climate strategy within the context of holistic climate management. Moreover, international guidelines such as PAS 2060 establish requirements for credible carbon neutrality (British Standards Institution, 2014), and the SBTi guidelines help define reduction targets and paths (Science Based Targets Initiative, 2021). Guidelines or targets were defined in all the sources examined, but how to select the measures to achieve these targets is generally unspecified. General guidelines are not sufficient to reduce the above described information deficits and uncertainties companies face. More concrete and at the same time company-specific selection procedures are needed.

There are different studies, where databased approaches or simulation models are mostly used for decarbonisation purposes in buildings. Amini Toosi et al. (2022) examined and quantified the potential of regenerative energies based solutions to mitigate GHGE in buildings. With the help of a machine learning based surrogate energy model, they come to the conclusion, that a coupled integrated photovoltaic and thermal energy storage system equipped with electric heat pumps can reduce GHGE by 21.42 % over 30 years of the building service life. Gao et al. (2023) used a multi-objective optimisation based model to investigate decarbonisation strategies for buildings. They showed results for the implementation for photovoltaic systems and the variation of indoor temperatures. Hiltunen et al. (2022) analysed different possibilities to decarbonise the heat demand of university campus buildings with the help of a simulation model. The greatest potential was shown for a low-temperature energy cascade connection to the city's network, which led to a reduction of GHGE by 955 tonnes CO_2e. Employing a multi-objective analysis approach, Kadrić et al. (2023) identified Pareto-optimal solutions for building retrofitting measures. Mainly, the upgrading of external walls and heat demand based energy efficiency measures were most effective regarding the mitigation of GHGE. Ligardo-Herrera et al. (2022) developed an open access planning tool to assess the effect of energy demand on GHGE of districts, buildings and house units. Their study concluded that providing smart tools is pivotal to planning nearly zero-energy districts. The simulation models relate primarily to renewable energies and renovation. The measures considered are therefore cross-sectional technologies with a focus on the building sector.

In addition, there are various simulation-based studies focusing on the industrial and energy sector. Iten et al. (2021) presented a data based framework to assess eco-efficiency improvements in manufacturing industries. With the help of a case study based in the processing of meat they showed the increase of eco-efficiency indicators for energy efficiency and renewable energy-based measures. The model supports the selection of measures but does not take energy and measure costs into account. Using an optimization model Wang et al. (2023) studied, how power generation companies are driven by economic and technological factors to adjust the allocation of their plants and how their profitability is affected. The scenarios of their case study showed, that achieving carbon neutrality 5–10 years ahead of time is financially and technologically feasible.

Borysiak et al. (2022) developed an algorithm that calculates the impact of green electricity and biogas on climate targets for industrial companies. It was found that digital solutions help meeting the targets. The premise is that any processes based on combustion are electrified and powered by green electricity. However, the Federal Network Agency's needs assessment counters that a grid expansion of this magnitude would only be realistic over a longer time horizon (Bundesnetzagentur, 2019). It follows that electrification alone, without raising energy efficiency potentials, does not offer a feasible solution. Ebersold (2022) developed a simulation model that enables an automated data-driven calculation of climate strategies. The selection of measures is based on the abatement costs (AC) and the industry of the respective company. The selection according to abatement costs enables a cost-benefit-efficient selection based on the data situation. However, it does not consider the frequency of implementation, which can be used as an indicator to measure transferability within the sector.

The research question addressed in this paper is: Can a data-driven model for computing sector- and company-specific decarbonisation strategies support or even replace the engineering development of a decarbonization strategy?

The novelty of this work is the development of an algorithm for computing decarbonisation strategies following a best-practice approach. This approach sorts the measures by sector and category, after which a selection is made based on the frequency of implementation instead of abatement costs or other economic and ecological factors in the respective sector. This approach is intended to increase the chances for implementation in individual companies due to the high transferability of the measures in the sector. It is therefore an optimization based on the probability of implementation. Framework conditions, climate targets and dynamic effects such as economic growth, changing emission factors (EF) and energy prices are considered. In addition, the reduction measures are calculated based on the sector as well as the energy data and preconditions of the company. In this way, a sector-specific decarbonisation strategy is developed in the first step, which can be further individualised through additional inputs, such as machines used or previously implemented measures. The algorithm's purpose is not to supplant energy consultants but to empower companies to develop an initial decarbonisation strategy independently and initiate steps towards it. Additionally, it aims to streamline the workload of energy consultants by automating measures with a high implementation frequency in the sector, thereby reducing consultation time and costs. With minimal data on a company, the industry, energy requirements and annual turnover, it is already possible to calculate a decarbonization strategy. More detailed data enables a more precise calculation with the model, but industry-specific average values are stored for all other key data in order to be able to develop measures even with a limited amount of information. This means that every company can receive an individual decarbonisation strategy with little effort. The model is intended to be a decarbonisation enabler for small and medium-sized enterprises. The results of the algorithm are presented for a plastic processing case study.

The paper is structured as follows: Section 2 presents the measure databases used and its preparation. Section 3 gives an overview of the materials and methods used. Section 4 presents the case study of a company in the plastics industry and a comparison with a manually calculated climate strategy. Section 5 contains the discussion of the results. Section 6 concludes with a summary and outlines potential directions for future research.

2. Dataset

The study uses the Industrial Assessment Center's (IAC) database as the primary data source. This database is supported and funded by the US Department of Energy. It provides a comprehensive data collection on energy efficiency, waste minimisation, and process optimisation, with over 19,460 assessments and 146,500 measure recommendations. Each measure includes costs, absolute savings of the respective energy sources and percentage savings in relation to the total demand of the company. In total, 193 different types of measures are included. SMEs from various industries can request an assessment. The analysis of processes, identification of improvement measures, and development of a list of measures are conducted by teams from 33 state-wide assessment centres affiliated with universities (IAC, 2023). In the model presented here, only the energy efficiency measures from the IAC data set are used. Measures for renewable energies are calculated separately and added to the strategy dataset. Compensation and carbon capture are currently not included.

The data preparation is based on Ebersold's (2022) approach. Several processing steps were performed to integrate this data into the developed model, which are described in this section. This method is applicable for every database with the needed Datapoints (implementation cost, energy savings, company energy demand, name and category of the measure). The raw data from the IAC was cleaned and adjusted using a Python code, which consisted of five main steps, as depicted in the flowcharts: 1) Upload of the IAC Database, 2) data preprocessing and adjustment, 3) input or selection of specific parameters, 4) further calculations, and 5) deletion of outdated measures. In **step 1**, the IAC data record in its original format, as of May 16, 2021, was read into separate spreadsheets and merged into a single data frame (DF) using the assessment ID (see Fig. 1).

While processing the DF in **step 2**, both assessments and individual measures are removed. The number of resulting assessments and measures is for each sub-step in Fig. 1 visible using the following Equations.

To use only up-to-date date, Measures (M) conducted prior to 2010 are removed by $M_{Year} \leq 2010 \rightarrow delete$. Furthermore, assessments that are not relevant to companies in the industrial sector were excluded. Both measures and assessments that show reductions of more than 100 % of the gas demand (W_{gas}), electricity demand (W_{el}) or summed demand (W_{sum}) were classified as incorrect and removed from the dataset by using $W_{gas} > W_{ges}$ *or* $W_{el} > W_{ges}$ *or* $W_{gas} + W_{el} > W_{ges} \rightarrow delete$. In addition, measures causing fossil fuel lock-ins and measures with an occurrence (n) of less than 5 times are removed by $n_M < 5 \rightarrow delete$.

The user-specific entry of energy costs, emission coefficients, and exchange rates are the subject of **step 3**. The entries are used subsequently calculate different key indicators. If no values are specified, the default values are used presented in Fig. 1.

In **step 4**, the measures are differentiated in organisational and technical measures. The lifetimes assigned to the organisational measures were taken from Deep (Glenting, 2020) and Brand (Brand, 2023). For technical measures, the service life is selected based on empirical values, which are also used in the calculation of depreciation for capital goods in Germany. Organisational measures do not have assigned lifetimes from depreciation. Thus, required rotations for various employee training courses are used. In the area of data protection, employee training should be implemented annually (DSGVO, 2019). However, there are also areas, such as standby management, where the rotations are longer. During further investigations, a conservative lifespan of one year and an optimistic lifespan of five years are considered for organisational measures that must be implemented regularly.

Step 5 contains the translation, analysis and assessment of the remaining different measures using the IAC manual (Muller et al., 2019). Due to the current state of the art and findings in the different technology sectors since the creation of the IAC manual 40 assessment recommendation codes (ARC) were excluded. A full list of the excluded ARC can be found in Table 4 in the Appendix. The resulting DF serves as a basis for obtaining information that can be used to reduce energy efficiency-related information deficits in industrial companies.

After cleaning the original data containing 146,500 measures, 28,984 remain as input for the simulation model as the processed DF in **step 6**.

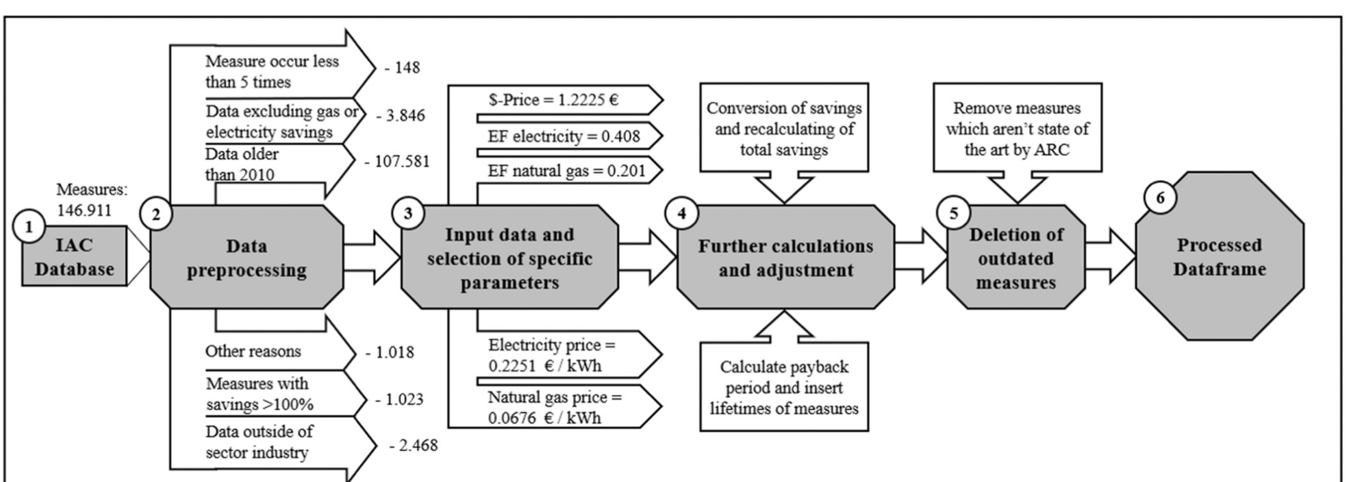

Fig. 1. Data Preprocessing of the IAC record. Step 1 is the deletion of measures which doesn't fulfil the framework conditions of the model. Step 2 and step 3 recalculate the savings and investment costs with German values. In step 4 outdated measures are removed to achieve the processed DF in step 6.

3. Methods

The simulation model based on Ebersold (2022) is used to identify the optimal selection of measures from the cleaned dataset to reduce Scope 1 and Scope 2 emissions. It consists of six main steps. In step 1, user or company-related data is entered. Fig. 2 shows the flow chart of the user input and the calculation of the strategy.

Only two energy sources, natural gas and electricity, are included within the model. The user input includes natural gas and electricity consumption, specific energy costs, energy consumption by application, industry sector, available area for photovoltaic systems, annual investment budget, EF for energy and goods and an estimated annual revenue growth rate. The model uses the next-event time progression method.

All the input parameters can be, if unknown to the user, filled by sector-specific averages (Rohde, 2016). In step 2, based on the selected industry, the industry specific sector code is used to filter the data set regarding measures that have been proposed or implemented by companies in this industry. The sector specific DF is split into subrecords for each application domain and saved in application-specific DFs. For example, the application domain "compressed air" for the sector "manufacture of plastic goods" includes 978 data samples, 13 unique measures and is based on the first 3 digits of ARC (2.42). The measures with the highest implementation rate for the recommendation DF are then selected from this subrecord. This process is repeated until the limit value is reached. **An** explanation of the limit value can be found in Eq. 2. Furthermore, in Step 2 the abatement costs (*AC*) are calculated. AC are costs incurred in reducing GHG in relation to a reference technology. They represent a relationship in terms of economic efficiency and ecological effectiveness when evaluating measures or alternative technologies. The calculation is carried out at this point to sort the measures according to avoidance costs in the first step. The measures are then selected from the industry-specific data set based on implementation frequency for the recommendation data set. Based on Hechelmann et al. (2023b), AC for a decarbonisation measure, even if the costs for the reference technology are unknown, can be calculated for a specific period that extends over several years (e.g. 2022–2035). In the initial stage, the abatement potential (AP_t) for each measure in year t is computed by summing the altered greenhouse gas emissions (GHGE) of energy source n. This calculation involves the emission factor ($EF_{n,t}$) of the year of simulation and the corresponding energy source and energy demand ($E_{n,t,0}$) before implementing the measure, as well as the values after implementation $E_{n,t,1}$), as depicted in Eq. (1). The resulting value is presented as the accumulated abatement potential in Eq. (2).

$$AP_t = \sum_1^N (EF_{n,t} * \quad E_{n,t,\quad 1}) - (EF_{n,t} * E_{n,t,\quad 0}) \tag{1}$$

$$sum\ AP_{2023\ldots ty} = \sum_{t=2023}^{ty} AP_t \tag{2}$$

Eq. (3) shows the calculation of the AC for year *t*. The inputs are the capital expenses C_c which are defined in this model as the implementation costs of the measures. C_r are accounted for in the fiscal year of implementation. C_r incurred due to increased energy demand in the initial state without mitigation measures. Therefore, C_r represent the savings of the measure to be implemented. and reduction of expenses in comparison to the relevant non-action scenario C_r, for example lower energy procurement or compensation costs, and the AP in year *t*. The price per kWh electricity is given individual by the user of the simulation model.

$$AC_t = \frac{C_c - C_r}{AP_t} \tag{3}$$

The capital expenditures for technical assets are determined by depreciating the investment costs using the guidelines for general-purpose fixed assets provided by the German Federal Ministry of Finance, if applicable (Federal Ministery of Finance, 2023). In cases where these guidelines are not applicable, a standard life expectancy of ten years is assumed. For organizational measures such as employee training, the estimated periods range from one to five years (Ebersold, 2022). Negative AC indicate that a measure recoups its costs within its anticipated lifespan. The mean AC are displayed as an average over the considered time, as shown in Eq. (4). Discounting is currently not taken into account. Depreciation is assumed to be linear over the lifetime.

$$mean\ AC_{2023\ldots ty} = \frac{\sum_{t=2022}^{ty} AC_t}{N_{years}} \tag{4}$$

By calculating the AC and AP for each individual year, dynamic effects can be considered. These dynamic parameters encompass the evolving German grid-average emission factor, projected according to as well as company-specific growth rates for turnover and energy demand.

Step 3 is dedicated to generating the recommendation dataset. The industry and application-related datasets resulting from step 2 are transferred to a company-related recommendation data set. Limit values (*LV*) are computed for each application domain (*a*) based on the energy reduction factor (*ERF*) and the energy demand (*W*) of the application domain. The percentage energy demand of each application domain can be found in Table 5 of the Appendix.

$$LV_{gas,a} = \quad W_{gas,\quad a} \times ERF_{gas,\quad a} \tag{5}$$

$$\boldsymbol{LV_{el,a}} = \quad \boldsymbol{W_{el,\quad a}} \times \boldsymbol{ERF_{el,\quad a}} \tag{6}$$

A set of measures is chosen for each energy source and application domain in consideration of the implementation frequency. For example, for the application domain "compressed air", the most frequently implemented measures are transferred to the recommendation data set, considering the sector code, until the defined efficiency potential is

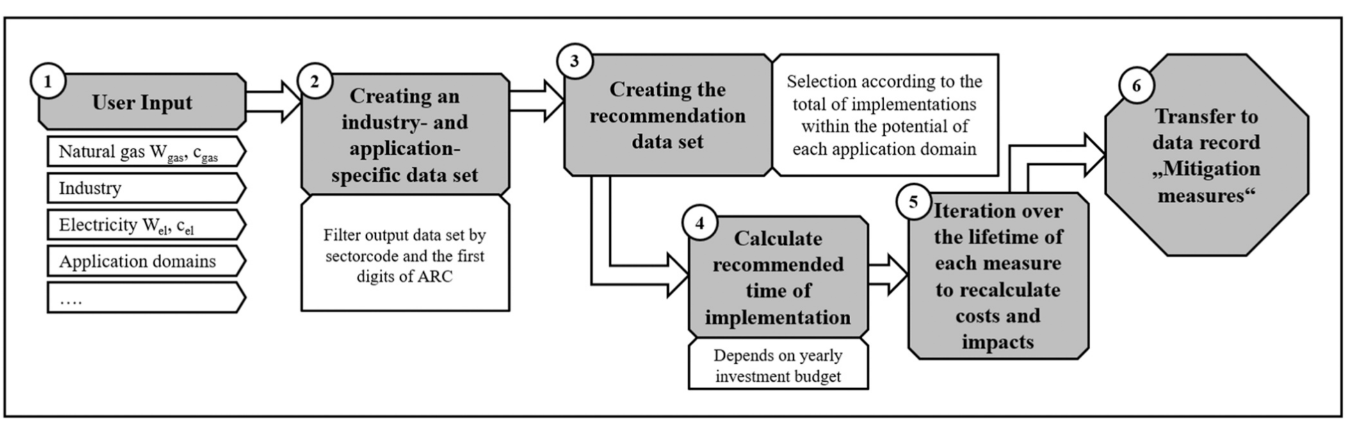

Fig. 2. Influence of user input to create an industry-specific dataset by creating subrecords for each application domain and subrecord. Afterwards a recommendation data set is created by using the total number of implementations of the measures.

reached. If a company does not require any energy for a particular application domain, the limit value is zero, and no measures are selected ($W_a = 0 \triangleq LV_a = 0$). E.g. for an insurance company, the limit value for compressed air would be zero. The technical potential of the selected measures is averaged and summed until the limit value for each application domain is reached, or all the measures related to the pertinent application domain have been queried. The chosen measures, along with their relevant parameters such as technical potential, implementation costs and service life, are then transferred to the recommendation dataset in step 3. This process is presented in Fig. 3.

The recommendation dataset exclusively contains measures related to energy efficiency and substituting fossile fuels resulting from step 2. Renewable energy plants are separately calculated using simplified framework conditions. Photovoltaic installations, for example, are estimated using the free space in m^2, the average energy generation per m^2 and the average costs per m^2. Other parameters like EF and specific costs for one kWh of electricity are within the defined framework of the simulation model.

The fourth step deals with the computation of the decarbonisation strategy by utilising company-specific input data and data from the recommendation dataset to simulate a climate protection strategy. The simulation model is event-discrete, i.e., when a particular event occurs, the simulation proceeds to a new period, and the variables are adjusted accordingly. The simulation period lasts till the target year, with a time step of one year, and various parameters change over time.

The Corporate Carbon Footprint (CCF) is recalculated in each time step. The following simplifications were adopted. The Scope 1 GHG E_{S1} result exclusively from the total demand for natural gas W_{gas} in each year j.

$$E_{S1,j} = W_{gas,j} \times EF_{gas,j} \tag{7}$$

Similarly, the Scope 2 GHG E_{S2} are calculated for the electrical energy requirement W_{el}.

$$E_{S2,j} = W_{el,j} \times EF_{el,j} \tag{8}$$

In step 5, the measure with the highest implementation rate from the recommendation data set is selected. The measure related GHGE reduction is calculated, using the EFs from Fig. 7 in the Appendix. This is repeated for each life year of the measure. If the sum of implementation costs of the measures in a single year expands the maximum annual expenditure specified in step 1 this measure will be implemented first next year. It is assumed that energy efficiency measures are considered state-of-the-art after implementation and are implemented again after the end of the service life. The measure i related GHGE reduction Δe is calculated with:

$$\Delta e_{i,j} = W_{el} \times AP_{el,i,j} + W_{gas} \times AP_{gas,i,j} \tag{9}$$

The operating income from returns OI_R for each measure i in each year j result from:

$$OI_{R,i,j} = \Delta W_{el,ij} \times c_{el,j} + \Delta W_{gas,i,j} \times c_{gas,j} \tag{10}$$

Finally, in step 6 the final data set "Decarbonisation strategy" is created, which contains the following output parameters for each year of the strategy:

- Corporate Carbon Footprint (CCF) according to Scope 1 and 2 with and without implemented measures for each year of the strategy,
- GHG reductions per measure,
- Sum of expenditures for energy efficiency and photovoltaics and
- Energy cost savings.

The simulated decarbonisation strategy provides a comprehensive overview of potential measures while requiring minimal user input. This final decarbonisation strategy can be further adjusted by the user to meet individual needs. This option offers scope to exclude non-existent technologies and methods and thus to optimize the composition of the decarbonisation strategy for the individual company.

4. Case study

A company assigned to the sector “manufacturing of plastic goods” serves as an exemplary case study. The production process includes the injection moulding of plastic components. The company-related energy demand information, that is used as an input parameter, is noted in Table 5 in the Appendix. The company had 800 m^2 of free roof space, suitable for photovoltaic installations. During the case study, a strategy is simulated for the period of 2022–2035 and compared with a strategy based on the results of an energy efficiency assessment by EnergieSchweiz (EnergieSchweiz, 2019). The strategy by EnergieSchweiz will be referred to as assessment strategy. All input parameters and conditions are assumed to be the same for both strategies. The used price per kWh of natural gas is 0.0676 €/kWh (Statista, 2023a) and for electricity 0.2251 €/kWh (Statista, 2023b). These prices are based on the 2022 German industrial price and are assumed to remain constant throughout the considered time period. Resulting from these inputs, the simulation model calculates a CCF of 1376 t CO_2e and energy costs of 757,754.30 € for the starting year.

4.1. Simulated strategy

A forecast of the development of the CCF with and without the implementation of measures is shown in Fig. 4. Scenario 1 covers the forecast of the CCF without the implementation of measures. Scenario 2 shows the forecast of the CCF under the condition that all measures of the simulated strategy are implemented.

The reduction in Scenario 1 is based on the emission trajectory of

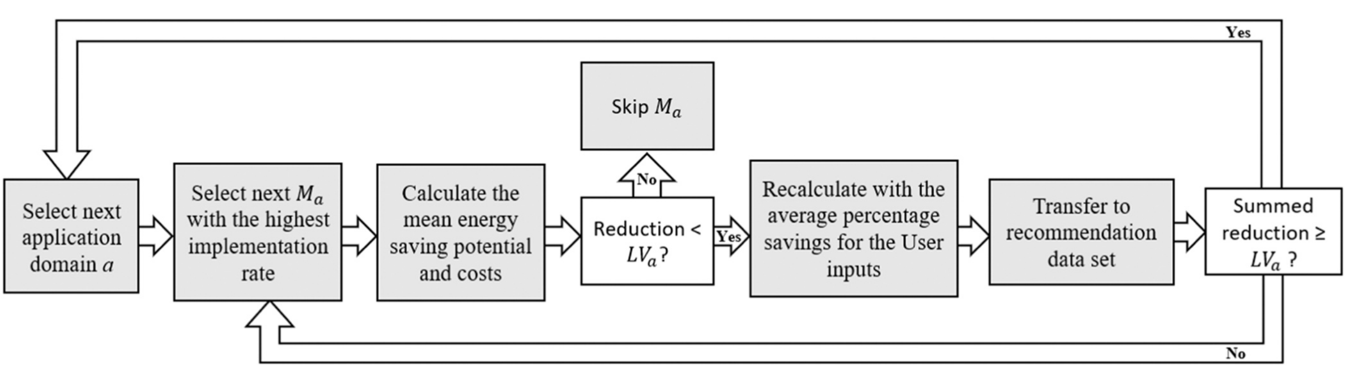

Fig. 3. Selection of measures for the recommendation data set for each application Domain by calculating the energy saving potential and costs. After recalculation the measure is transferred to the recommendation data set and the next measure or application domain is chosen, depending if the summed reduction exceeds the limit value of the application domain.

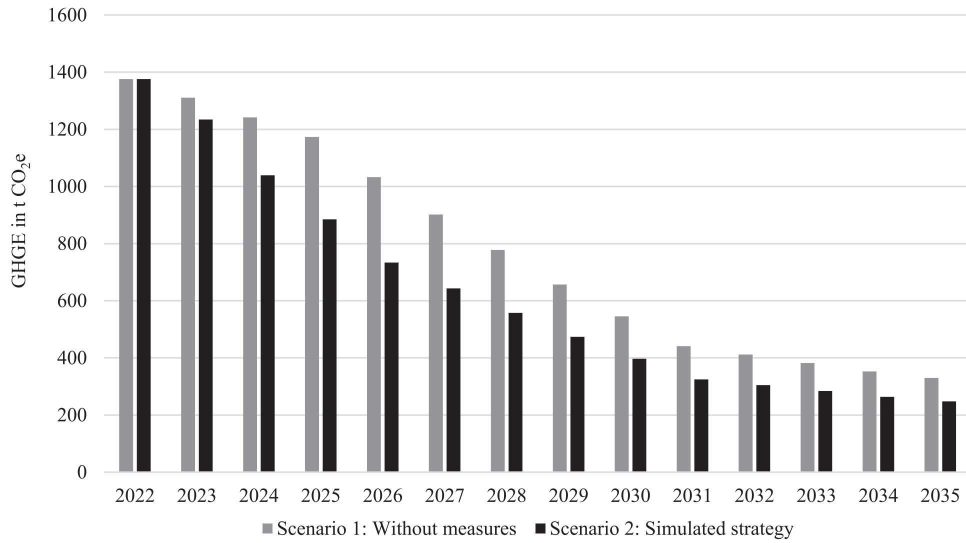

Fig. 4. Forecast of the CCF for the company in the case study. Scenario 1 shows the trajectory for the CCF with no decarbonisation measures applied. The CCF changes without measures due to the assumed reduction of the grid-average emissions. Scenario 2 shows the CCF forecast for the strategy developed with the simulation model.

Prognos (2021) and Hechelmann et al. (2023a) that the German grid-average EF will decrease over time. As shown in Fig. 7 it is expected to decrease rapidly from 421 gCO_2e / kWh in 2022–181.3 gCO_2e / kWh by 2030 and 33.8 gCO_2e / kWh by 2040. For natural gas, a constant EF of 201 gCO_2e / kWh is applied (Lauf et al., 2022). Scenario 1 starts with a CCF of 1376 tCO_2e in 2022 and ends with 330 tCO_2e in 2035.

The simulated strategy includes 13 measures. They are implemented in the years 2023 – 2026 and lead to an absolute reduction of 19.9 % compared to the GHGE without measures. The recommended measures are primarily assigned to the optimisation of production facilities. Further measures concern the application domains lighting, cooling, compressed air, air conditioning and energy generation. A list of the measures is given in Table 1. Scenario 2 achieves a CCF of 248.0 tCO_2e in 2035.

The AC are calculated for the period from the year of implementation to 2035. The AC for all measures, except the installation of roof top photovoltaics, are negative. This results from the fact that the expected savings until 2035 exceed the implementation costs of the measures. The order of the measures is based on the boundary conditions of the model, it was set that a new measure is implemented in the next year if the annual investment costs exceed 60,000 €. The maximum number of annual measures has been limited to five to ensure an implementation within the company's capacities.

4.2. Verification of the results

In this section, the verification of the simulated strategy is demonstrated through a comparison with the assessment strategy developed manually. Previously, manual tests and extreme value analyses were conducted to validate the model. All framework conditions are assumed to be the same. The assumed energy savings were fully obtained from the published strategy of EnergieSchweiz. The resulting GHGE reductions are based on the same EFs as used in the simulated strategy, stated in the beginning of the section. A forecast of the development of the CCF for Scenario 3 and Scenario 2 is shown in Fig. 5. Scenario 3 covers the forecast of the CCF with the implementation of all measures recommended in the assessment strategy. Scenario 2 shows the forecast of the CCF under the condition that all measures of the simulated strategy are implemented.

The decarbonisation strategy of EnergieSchweiz is based on nine measures. They are implemented in the years 2023 – 2028 and lead to an absolute reduction of 17,8 % compared to scenario 1. A comparison with scenario 2 shows, that the GHGE reductions are approximately even. The summed GHGE reduction differs by 2.1 %. The recommended measures are primarily assigned to the area of production. Further measures are assigned to the sub-categories hot water, cooling, compressed air, air conditioning, substitution, and energy generation. A complete list of the measures can be found in Table 2. Scenario 3 achieves a CCF of 220.5 tCO_2e in 2035.

As no implementation costs were indicated by EnergieSchweiz no avoidance costs are calculated for the comparison strategy of the assessment.

Inherent to each strategic approach are distinct measures that are exclusive to that strategy. However, there also exist shared measures that exhibit similarities across both strategies. Measurement 2.3, 2.7, 2.8 and 2.9 of the assessment strategy do not coincide with the measures of the simulated strategy. These measures are not included in the database. Furthermore, measures that adapt existing processes or employee training are not considered within the scope of the assessment strategy. Each measure addresses newly acquired devices. Therefore, there is no overlap between measures 1.1, 1.4, 1.5 and 1.8 of the simulated strategy, which concern employee behavior and process adjustment. The comparable measures and the resulting GHGE reductions, assuming simultaneous implementation in 2025, are shown in Table 3.

Measure 2.1 and 2.2 of the assessment are comparable to measure 1.10 and 1.11 of the simulated strategy. The resulting GHGE reduction differs depending on the strategy. Measure 2.1 is implemented in 2023 and reduces the GHGE by 493 tCO_2e. Measure 1.11 is implemented in 2025 and reduces the GHGE by 392.5 tCO_2e. By excluding the years 2023 and 2024 for measure 2.1, 355.4 tCO_2e are reduced. The difference between both measurements is a 9.5 % lower GHGE reduction in the assessment strategy. A full list of the reduction per year can be found in

Table 1
Measures identified with the simulation model.

No.	Year	Measure	GHGE reduction till 2035 in tCO_2e	Implementation costs in €	AC in € / tCO_2e
1.1	2023	Use the highest possible cooling water temperature	122.6	362.8	-574.9
1.2	2023	Use adjustable frequency drive in existing systems	170.6	49,535.4	-287.4
1.3	2023	Eliminate leaks in compressed air lines / valves	101.3	1,3826.0	-441.3
1.4	2023	Analyse exhaust gases for appropriate air / fuel ratio	74.6	1713.3	-554.9
1.5	2023	Ventilation system to shut off when room is not in use	64.0	350.9	-572.4
1.6	2024	Use cooling tower or economizer as a substitute for chiller cooling	365.4	14,698.3	-1115.7
1.7	2024	Use higher efficiency lamps and/or ballasts	109.6	9958.7	-487.1
1.8	2024	Set up preventive maintenance programme	50.2	843.0	-561.2
1.9	2024	Photovoltaic on roof surfaces (133 kWp)	303.8	186,200.0	35.0
1.10	2025	Replace existing chiller with a high efficiency model	161.6	8007.8	-522.2
1.11	2025	Use high efficiency electro motors instead of hydraulic models	392.5	58,189.8	-423.5
1.12	2026	Replace oversized motors and pumps with suitable sizes	164.8	6794.8	-514.0
1.13	2026	Install motor voltage regulator on lightly loaded motors	88.8	7760.0	-467.8

Table 7 and Table 8 in the Appendix. For Measurement 2.2 the GHGE reduction till 2035 is 161.6 tCO_2e. The same measurement 1.10 reduce the GHGE by 141.01 tCO_2e. If the reductions are calculated for the same year of implementation, the GHGE reduction of measure 2.2 is reduced to 109,7 tCO_2e. The same measurement calculated by the simulation, based on average values, results in a 47.3 % higher GHGE reduction. Measure 1.9 and measure 2.4 are also comparable. The resulting GHGE reduction is nearly equivalent. The assessment strategy has a lower reduction of 5.3 % GHGE. Measures 1.6 and 2.5 are also comparable. Both concern the purchase of a free cooler. The GHGE reduction differs by 34.6 tCO_2e. This means a higher GHGE reduction of 11.3 % percent for the same measure in the assessment strategy. The mentioned comparisons of similar measures and a comparison of all other measures in Scenario 2 and Scenario 3 are presented in Fig. 6.

The comparison of the other measures shows that they reach in total 9.5 % lower GHGE reduction in the assessment strategy. In the simulated strategy, many smaller measures with low potential are implemented, while in the assessment strategy measure 2.6, direct heat transport accounts for 60.2 % of the savings.

5. Discussion

Overall, the reduction potential of the simulated strategy and assessment strategy differ only slightly and show a high level of consistency. There are differences in the choice of individual measures. Due to the high bandwidth of possible measures, there are many possible combinations of mitigation measures. It should be noted that the assessment strategy is precisely tailored to the assessed injection molder, while the simulated strategy is based on the dataset and the input industry “manufacture of plastic goods”. Nevertheless, the model can be used complementary to an existing decarbonisation strategy. The measures suggested by the model differ usually from the measures of the assessment strategy. The model can therefore be used to revise existing decarbonisation strategies, but also to develop an initial strategy. To implement a more precise subdivision of the sector, more data of injection molder assessments is needed. More data from conducted assessments strengthens the robustness of the model and the level of detail of the industries can be improved. This means that, for example, companies from the “manufacture of plastic goods” sector can currently be simulated, but a higher data resolution would also make it possible to narrow down to injection molders. To obtain reliable results for this case, enough other injection molders must already be included in the data set. Further subdivision possibilities would be the number of employees and the annual turnover, to make a classification according to the size of the company. Even if the average distribution of energy requirements in a sector provides an important indication of the largest energy consumers, each company remains unique. When using it for a company, the energy requirements must be entered manually according to application domain to achieve reliable results.

Besides the sector specification, the differences between the assessment strategy and the simulated strategy can be traced back to another procedure of the simulation model. Within the framework of the simulation, companies can specify the percentage distribution of energy requirements according to application domains or use sector-specific average values. Except for photovoltaics, the measures are limited to efficiency measures in these application domains. These already cover a high proportion of the savings potential, but further measures exist outside the defined areas of application. These could be integrated into the model in the future. In this context, an application domain independent best practice category is also conceivable. This category would include those measures that have not yet been listed but are frequently implemented in the sector and are not part of any of the considered application domains.

5.1. Limitations and boundaries of the simulation model

Feedback effects between and interdependencies of measures are neglected in the simulation. With the same measures, the GHGE reduction potential corresponds with a maximum deviation of 10.11 % compared to the assessment strategy if measure 1.10 is excluded. The deviation of measure 1.10 results from feedback effects with measure 1.6. The assessment strategy includes the reduced cooling demand due to the free cooler in their design of the of the new chiller. The calculated energy and cost savings always refer to the initial values of the start year. If there are reduced energy requirements for previous years, this change is currently not considered.

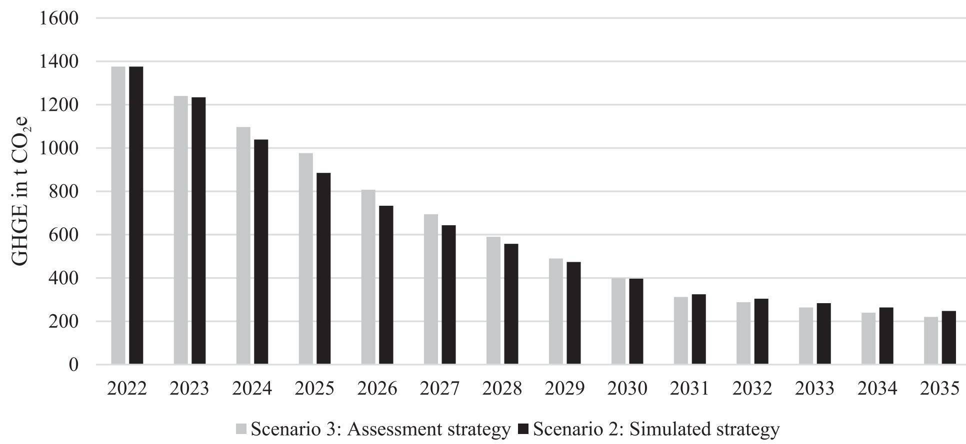

Fig. 5. Comparison of the CCF forecasts for the simulated and the manually developed strategy by EnergieSchweiz. The latter was prepared by energy consultants.

Table 2
Assessment decarbonisation strategy.

No.	Year	Measure	GHGE reduction till 2035 in tCO_2e
2.1	2023	Machine replacement (injection molding machine)	493.0
2.2	2024	Machine replacement (process cooling)	130.2
2.3	2024	Peak load coverage (air conditioning)	79.9
2.4	2024	Photovoltaic on roof surfaces (136 kWp)	287.8
2.5	2025	Direct freecooling	342.5
2.6	2026	Direct heat transport	410.4
2.7	2026	Waste heat utilisation (compressed air)	141.0
2.8	2027	Air-to-water heat pump	48.4
2.9	2028	Integrating of hot water into the heating circuit	8.3

Since the database is based on assessment data, carried out by experts, it can be assumed that the greatest savings potentials were usually identified and directly addressed by recommending company-specific measures. For the individual companies, this procedure represents the most efficient solution, but regarding the simulation model, this can lead to overrated savings achieved by a measure. For example, this could be due to an outdated reference technology. If a company has been using a compressor for 35 years, a renewal will lead to significantly higher savings than would be the case for an average company. Thus, the AC are set too low and the transfer of the measure to a third company results in significantly lower savings and thus higher AC. It is crucial to acknowledge that measures exhibiting negative AC should not be evaluated solely based on their avoidance costs. As depicted in Eq. (2), increased cost-effectiveness can lead to negative avoidance cost, but negative avoidance cost limiting the explanatory power of avoidance costs. Since energy efficiency measures make up for a large share of the measures, negative avoidance costs correspond to the expected result. (IEE, 2020) It should be noted that the potentials contained in the database represent only a small excerpt of all existing measures for decarbonisation strategies. The basis of the IAC database are audits for American companies. The transfer to other regions in the world harbours the risk of unsuitable investment costs for the different markets in the world. Energy saving potentials for processes and cross-sectional technologies can be transferred with the mentioned restrictions.

Within the model the company's inventory, like technical equipment or building stock, and energy requirements are only affected by the recommendations of the simulation model. Effects like an energy crisis cannot be foreseen and are thus not covered by the model. This is also the case for economic growth, which is represented through a constant annual growth rate only.

6. Conclusion

The developed simulation model offers a supporting tool for companies to identify approaches for minimising and avoiding GHGE and to overcome information deficits. The used dataset, obtained from practical experience, enables the selection of the most common measures within the sector of the user of the simulation model. Long-term decarbonisation strategies can be derived by allocating the energy requirements according to the defined areas of application and by including forecasts up to the year 2035. The results of the model, in the form of sector-specific proposals for action up to the year 2035, can be used to examine and calculate individual investment options. Companies can use the sector specific decarbonisation strategy to get started with their own decarbonisation strategy and individualise the results of the simulation to their specific needs. In the future, the model could be extended to other sectors. In conclusion, the simulation model already

Table 3
Comparable measures resulting from the simulation and the assessment.

Year	Simulation strategy			Assessment strategy			Comparision
	No.	Name	GHGE reduction	No.	Name	GHGE reduction	Percentage deviation
2025	1.6	Use cooling tower or economizer as a substitute for chiller cooling	307.8	2.5	Direct freecooling	342.5	+11.3 %
2025	1.9	Photovoltaic on roof surfaces (133 kWp)	255.9	2.4	Photovoltaic on roof surfaces (136 kWp)	242.4	-5.3 %
2025	1.10	Replace existing chiller with a high efficiency model	161.6	2.2	Machine replacement (process cooling)	109.7	-32.1 %
2025	1.11	Use high efficiency electro motors instead of hydraulic models	392.5	2.1	Machine replacement (injection molding machine)	355.4	-9.5 %

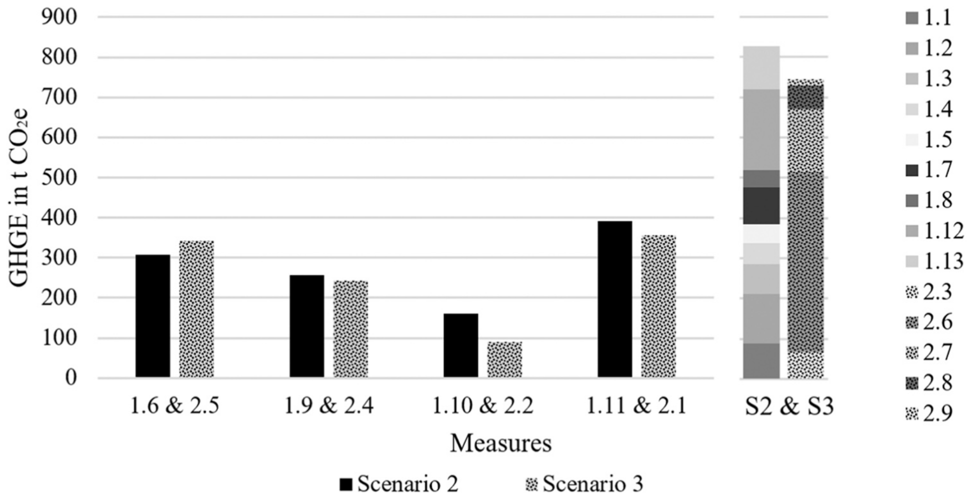

Fig. 6. Comparison of the similar measures and the sum of all remaining GHG mitigation measures in Scenario 3 and Scenario 2.

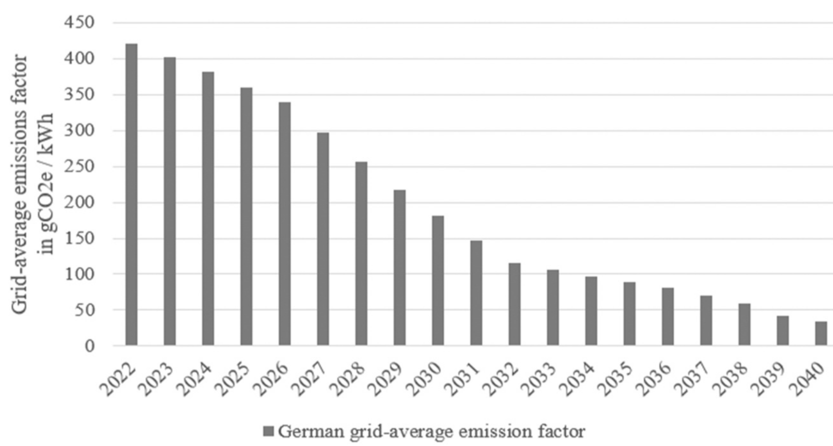

Fig. 7. Assumed trajectory for the German grid-average emission factor.

offers a basis for identifying approaches and opportunities for the implementation of an individual decarbonisation strategy. The knowledge of existing efficiency potentials as well as the inclusion of developments based on existing forecasts offer companies the opportunity to develop a sustainable decarbonisation strategy.

Before implementation, additional research on average sector application domain energy demands is needed to increase the accuracy of the suggested saving potentials. Additionally, more assessment data, particularly from other countries, are needed. The results of the simulation model are limited to scopes 1 and 2 within a climate strategy. For a complete decarbonisation strategy, measures for the upstream and downstream supply chain (scope 3) are required. Provided data is available, the method of the algorithm is transferable to scope 3. An extension of the observation period to 2045 / 2050 is also conceivable to simulate the climate strategy until the latest point in time at which CO_2e neutrality is achieved.

To improve the model, additional measure data can be combined with the IAC database. The more strategies are created with the model and subsequently personalized by users, the more accurate the measures will become for specific industries. A supervised learning approach should be applied in the future to enhance the action recommendations. In the future, other energy sources will be included in the simulation. In addition, carbon capture and compensation will be integrated for the last step. Furthermore, additional sectors and companies are to be included in the future to enable a complete validation of the model.

CRediT authorship contribution statement

Felix Ebersold: Writing – review & editing, Software, Data curation. **Ron-Hendrik Hechelmann:** Writing – review & editing. **Aaron Paris:** Writing – review & editing. **Jannik Oetzel:** Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

I have shared the link to the datasource at the Attach File step

Appendix

Table 4
Deleted assessment recommendation codes (ARC).

Deleted ARC measures			
2.1221	2.3411	2.6211	2.7272
2.1222	2.3412	2.6221	2.7273
2.1223	2.3414	2.6231	2.7291
2.1224	2.3416	2.6241	2.7293
2.1321	2.4152	2.6272	2.7411
2.1322	2.4154	2.6291	2.7425
2.1392	2.4322	2.6293	2.7441
2.2123	2.4323	2.7144	2.7444
2.3192	2.5194	2.7244	2.7494
2.3311	2.6125	2.7245	2.7495

Table 5
Company Energy data.

Natural Gas	Quantity	Unit	
Boiler	324.000	kWh / year	
Electricity	**Quantity**	**Unit**	**Percentage**
Injection Molding Machines	2.310.000	kWh / year	71 %
Air Conditioning	347.000	kWh / year	11 %
Process Cooling	308.000	kWh / year	9 %
Other	158.000	kWh / year	4,80 %
Compressed Air	138.000	kWh / year	4 %
Hot Water	8.000	kWh / year	0,20 %
Sum	3.269.000	kWh / year	100 %

Table 6
Assumed trajectory for the German grid-average emission factor.

Year	German grid-average emission factor
	(gCO_2e/kWh)
2022	420,7
2023	401,2
2024	381,1
2025	360,3
2026	338,7
2027	296,3
2028	256,0
2029	217,7
2030	181,3
2031	146,6
2032	115,5
2033	105,7
2034	96,7
2035	88,4

Table 7
GHGE in t CO_2e for each year and measurement of the simulation model strategy.

Year	without measures	with measures	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	1.9	1.10	1.11	1.12	1.13
2022	1375.99	1375.99													
2023	1310.61	1234.41	17.53	24.38	14.48	10.67	9.14								
2024	1241.96	1039.28	16.56	23.04	13.68	10.08	8.64	57.60	17.28	7.92	47.88				
2025	1173.32	884.83	15.59	21.70	12.88	9.49	8.14	54.24	16.27	7.46	45.09	28.48	69.16		
2026	1032.75	733.49	13.62	18.94	11.25	8.29	7.10	47.36	14.21	6.51	39.37	24.86	60.38	30.78	16.58
2027	901.99	643.17	11.78	16.38	9.73	7.17	6.14	40.96	12.29	5.63	34.05	21.50	52.22	26.62	14.34
2028	777.77	557.37	10.03	13.95	8.28	6.10	5.23	34.88	10.46	4.80	28.99	18.31	44.47	22.67	12.21
2029	656.81	473.82	8.33	11.58	6.88	5.07	4.34	28.96	8.69	3.98	24.07	15.20	36.92	18.82	10.14
2030	545.67	396.46	6.76	9.41	5.59	4.12	3.53	23.52	7.06	3.23	19.55	12.35	29.99	15.29	8.23
2031	441.06	324.33	5.29	7.36	4.37	3.22	2.76	18.40	5.52	2.53	15.30	9.66	23.46	11.96	6.44

(*continued on next page*)

Table 7 (*continued*)

Year	without measures	with measures	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	1.9	1.10	1.11	1.12	1.13
2032	411.64	304.05	4.88	6.78	4.03	2.97	2.54	16.96	5.09	2.33	14.10	8.90	21.62	11.02	5.94
2033	382.22	283.76	4.46	6.21	3.69	2.72	2.33	15.52	4.66	2.13	12.90	8.15	19.79	10.09	5.43
2034	352.80	263.48	4.05	5.63	3.34	2.46	2.11	14.08	4.22	1.94	11.70	7.39	17.95	9.15	4.93
2035	329.91	247.70	3.73	5.18	3.08	2.27	1.94	12.96	3.89	1.78	10.77	6.80	16.52	8.42	4.54
Sum	**10934.49**	**8762.15**	**122.59**	**170.56**	**101.27**	**74.62**	**63.96**	**365.44**	**109.63**	**50.25**	**303.77**	**161.62**	**392.50**	**164.84**	**88.76**

Table 8
GHGE in t CO_2e for each year and measurement of the assessment strategy.

Year	without measures	with measures	2.1	2.2	2.3	2.4	2.5	2.6	2.7	2.8	2.9
2022	1375.99	1375.99									
2023	1310.61	1310.61	70.49								
2024	1241.96	1241.96	66.60	20.52	12.60	45.36					
2025	1173.32	1112.97	62.72	19.32	11.87	42.71	60.34				
2026	1032.75	926.43	54.76	16.87	10.36	37.30	52.69	38.98	14.65		
2027	901.99	797.66	47.36	14.59	8.96	32.26	45.57	39.58	14.49	4.70	
2028	777.77	677.81	40.33	12.43	7.63	27.47	38.80	40.15	14.34	4.92	1.74
2029	656.81	563.11	33.49	10.32	6.34	22.81	32.22	40.70	14.19	5.15	1.45
2030	545.67	457.71	27.20	8.38	5.15	18.52	26.17	41.21	14.06	5.35	1.18
2031	441.06	358.51	21.28	6.56	4.03	14.49	20.47	41.69	13.93	5.54	0.92
2032	411.64	330.61	19.61	6.04	3.71	13.36	18.87	41.83	13.89	5.60	0.85
2033	382.22	302.71	17.95	5.53	3.40	12.22	17.27	41.96	13.86	5.65	0.78
2034	352.80	274.81	16.28	5.02	3.08	11.09	15.66	42.10	13.82	5.70	0.70
2035	329.91	253.11	14.99	4.62	2.84	10.21	14.42	42.20	13.79	5.75	0.65
Sum	**10934.49**	**8993.08**	**483.5**	**130.20**	**493.03**	**130.19**	**79.94**	**342.47**	**8.26**	**410.39**	**287.78**

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