Environomic optimisation of local energy concepts for utility companies under the influence of increased energy prices

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Abstract:

In the light of the current gas crisis, decentralisation and decarbonisation of building heat systems has received another drive. Utility companies must adapt their product strategy while regarding both economic and environmental criteria. In this study, we therefore optimise the layout and operation of different building heat systems. We analyse four different energy systems with a fixed composition of technologies for the space heating and hot water supply of a typical multi-family house in Düsseldorf, Germany. The concepts are modelled as MILP optimisation problems with the oemof-based framework ESyOpT®. The objective is to minimize the total costs and in addition, in a multi-objective approach we limit the system's CO_2 emissions to 90 % of the cost-optimal solution. To investigate the effect of increasing energy prices, we optimise for a 2021 scenario and a 2022 scenario. We find that a reduction of CO_2 emissions by 10 % leads to a cost increase of 7-51 % in 2021. For 2022, the cost increase is only 4-23 % but at a much higher cost level. The resulting optimised systems are assessed and ranked under the metrics of the total annual costs and the total direct annual CO_2 emissions using three different methods for multi-criteria decision analysis. The results show that the system consisting of a pellet boiler, a solar thermal collector and a heat storage performs best. In fact, this system is the most robust to the price increase and a change in the criteria weights.

Keywords: energy system optimisation, building energy system, heat system, utility companies, gas crisis

1 Introduction

The current gas crisis has intensified the pressure on utility companies to enforce the decentralisation and decarbonisation of the energy system [1]. They are facing high energy prices and an increasing interest in alternative heat supply systems while the focus is on the security of supply, especially for residential buildings. Utility companies used to measure their success by only economic criteria, however, environmental criteria have become an important metric adjacent to the economic parameters.

We therefore investigate the performance of pre-selected heat energy systems regarding economic and environmental (environomic) criteria. These environomic metrics are obtained

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via a mathematical optimisation of the energy systems under either a single objective, the total annual system costs, or a multi-objective approach with an additional constraint on the total direct CO_2 emissions of the system. The effect of increasing energy prices is examined by comparing the results of a 2021 dataset and a 2022 dataset for energy prices.

1.1 Research questions

In this study, we perform a holistic energy system analysis by regarding environomic criteria for the assessment as well as objectives for the mathematical optimisation. We thus investigate the following research questions:

- By how much do the total annual system costs increase if the systems' direct CO_2 emissions are limited to 90 % of the emissions of the cost optimal solution?
- How do increasing energy prices affect this trade-off?
- Which system/concept performs best according to environomic criteria?
- How does the assessment ranking differ under the use of different analysis methods?
- How robust are the ranking results under changing criteria weights?

1.2 Scope of the study

The used methodology and the theoretical background of the performed energy system analysis are presented in Chapter 2. Moreover, the case study, including the relevant datasets are introduced in Chapter 3. Subsequently, the results of the optimisation and the multi-criteria assessment are presented in Chapter 4 and concluded in Chapter 5.

2 Methodology

The methodology used in this study can be divided into the used optimisation methodology and the used multi-criteria decision analysis methodology. Those two forms of energy systems analysis are performed successively and applied to the heat energy systems. The methodology is summed up in Figure 1 and each process step is explained in further detail in the following sections.

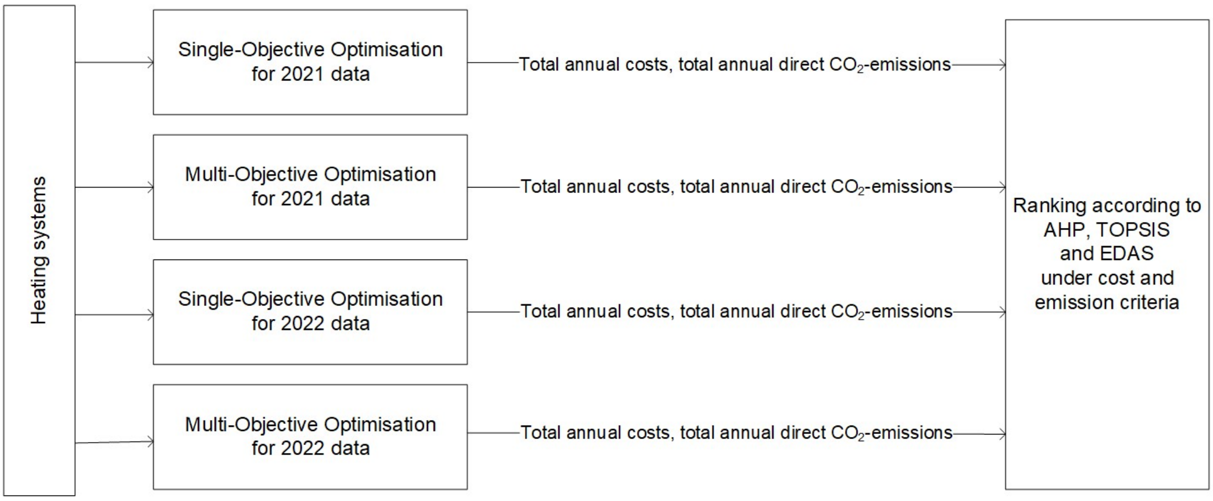

Figure 1: Process steps of the methodology

2.1 Mathematical optimisation

The concepts are modelled as mixed integer linear programs (MILP) with ESyOpT® which is a modelling tool based on the python package oemof [2]. The proposed optimisation problem is solved by the Gurobi solver [3] with a branch-and-cut algorithm.

The gas and electricity grids as well as the solar thermal collector are modelled as sources. The normalised heat output for $1m^2$ of the thermal collector is calculated using a pvlib-python model [4]. The household demands for space heating and hot water are represented as sinks.

To implement the other components, we use the class Transformer provided by oemof to write our own models. The models are briefly described in the following:

Since we perform a design optimisation for the concepts, the decision variables of the optimisation problem are the sizes of the systems components along with their operation. The operation of all components is limited by a maximum power rating, $P_{max,power\ rating}$, which itself is a decision variable. To limit the solution space the maximum power rating is restricted by a minimum and maximum selectable size given as a parameter.

$$P_{min} \leq P_{max,power\ rating}(t) \leq P_{max} \tag{1}$$

For the boilers, heat pump and the heat storage P_{max} is chosen arbitrarily large, for the solar thermal collector the roof size sets this limit. P_{min} is a small value and chosen for each component individually such that an installation according to the energy concept is ensured.

The models of the boilers and the heat pump additionally include a minimum part load (MPL) constraint, which constricts the operation of these components further.

$$Y_{op}(t) \cdot P_{max,power\ rating} \cdot MPL \leq P_{out}(t) \leq P_{max,power\ rating}\ , \tag{2}$$

where $Y_{op}(t)$ is a binary variable indicating whether the component is operating in timestep t.

The coefficient of performance (COP) of the heat pump is modelled as being dependent on ambient and supply temperature, whereas the boilers have constant efficiencies.

The heat storage is implemented with two types of losses: Firstly, capacity dependent losses and secondly storage level dependent losses. Furthermore, charging and discharging in the same timestep is forbidden.

In the study at hand, we first follow a single-objective optimisation approach. To do so, the system's total annual costs (TOTEX) are minimised as given in Eq. (3).

$$\min(TOTEX_{annual}) = \min(CAPEX_{annual} + OPEX_{annual}) \tag{3}$$

The total costs consist of the expenditures for the investment of the new installation of technologies (CAPEX) and the operation costs (OPEX) which are calculated from the fuel and electricity costs as well as maintenance costs. The expenditures for investment are discounted over the lifetime of the technology to the year of investment.

$$CAPEX_{annual} = CAPEX_{total} \cdot \frac{WACC \cdot (1 + WACC)^{LIFETIME}}{(1 + WACC)^{LIFETIME-1}}\ , \tag{4}$$

with WACC being the weighted average cost of capital.

To linearise the mostly non-linear relationship between the components size and its price, the $CAPEX_{total}$ is calculated using a fixed price part C_{fix} and a size variable price part $C_{variable}$.

$$CAPEX_{total} = C_{fix} + C_{variable} \cdot P_{max,power\ rating} \cdot \qquad (5)$$

In the case of multi-objective optimisation, an epsilon constraint is used to limit the direct CO_2 emissions. Using this method, the objective function is the same as, in the cost minimisation, but an additional constraint restricting the CO_2 emissions by a hard limit reduces the solution space of the optimisation problem. For the given study, we choose a limitation of 10 % of the CO_2 emissions from the cost optimal solution. Therefore, the following solution to the energy systems will have only 90 % of the emissions regarding the cost optimal case, but at the expense of higher system costs since the two objectives are competing. The goal is to investigate the marginal costs for 10 % emission savings for each of the alternatives and scenarios.

2.2 Multi-criteria decision analysis

The resulting concepts are assessed and ranked under the metrics of the total annual costs and the total direct annual CO_2 emissions. In order to compare the alternatives by only a single metric, we use multi-criteria decision analysis (MCDA) methods. The goal is to obtain one performance score for each alternative by which they can be sorted. Hence, methods that follow a Full Aggregation Approach [5] can be used. The three chosen methods for this study are the Analytic Hierarchy Process (AHP) [6, 7], Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [8, 9] and Evaluation Based on Distance from Average Solution (EDAS) [8, 10] since they all give a performance score for each alternative while using different approaches. From an algorithmic point of view, TOPSIS and EDAS are more similar to each other than AHP to either of them.

2.2.1 Analytical Hierarchy Process

The AHP was first introduced by Saaty [7] as a method of measurement with ratio scales. The method can be used for both criteria weight determination and alternative assessment. Its basis is a fundamental scale (Table 1) by which the preferences of the criteria and the alternatives concerning the criteria are identified via pair comparisons.

Table 1: The AHP scale adapted from Saaty [7]

Absolute scale	Definition	Explanation
1	Equal importance	Two activities contribute equally to the objective
3	Moderate importance of one over another	Experience and judgement moderately favour one activity over another
5	Essential or strong importance	Experience and judgement strongly favour one activity over another
7	Very strong importance	An activity is strongly favoured, and its dominance demonstrated in public

9	Extreme importance	The evidence favouring one activity over another is one of the highest possible orders of affirmation
2, 4, 6, 8	Intermediate values between the two adjacent judgements	When compromise is needed

For the first step of applying the method, the determination of the criteria weights, a pair of criteria *(i, j)* is compared according to the AHP scale. If *i* is preferred over *j*, the value in the pair comparison matrix takes the value v_{AHP} from the scale: $a_{ij} = v_{AHP}$ while $a_{ji} = \frac{1}{v_{AHP}}$ and vice versa. Note that all $a_{ii} = 1$. The eigenvector of the first eigenvalue of the pair comparison matrix equates to the criteria weights. This method for the determination of criteria weights is used in this study and the results of the application are presented in Chapter 4.2.

In the second step of applying the AHP method, the alternatives are assessed according to the criteria and their weights. If the criterion is qualitative, the algorithm goes equivalent to the process of weight determination. The alternatives are pairwise compared concerning the criteria according to the AHP scale and the pairwise comparison matrix is built. The first eigenvector of this matrix is calculated for all these qualitative criteria and saved for the next step of the algorithm. The procedure for quantitative criteria deviates from the above-described step in the sense that the normalised vector is built from the alternatives' values for the given criterion. In case the quantitative criterion has a negative ordered scale (meaning, a lower value is preferable), the alternatives' values need to be inverted in a first step, so that the highest value of the normalised vector corresponds to the best parameter value for the given criterion.

The matrix of the vectors for all the (qualitative and/or quantitative) criteria is eventually multiplied with the weights vector from the first step of the method. The performance score indicates the multi-criteria metric for each alternative and ranking of the alternatives follows these performance scores with the best alternative being the one with the highest score.

2.2.2 Technique for Order Preference by Similarity to Ideal Solution

This method for MCDA was first introduced by Hwang et al. [9] and the resulting ranking of alternatives is based on an overall performance score of each alternative. The performance score measure represents the relative distance to a hypothetical solution which consists of the worst value for each criterion among all the values of the alternatives. The method application is well described in [8]. In order to apply the method, the criteria weights w_j need to be given.

For this method, the first necessary step is the building of the decision matrix with the values x_{ij} of all $i = 1, \dots, m$ alternatives for each criterion $j = 1, \dots, n$. Based on the x_{ij}, a normalised decision matrix is calculated, dividing each x_{ij} by the square root of the sum of squares and multiplying with the weight w_j of the criterion.

$$x_{ij}^{*} = w_j \, \frac{x_{ij}}{\left(\sum_{i=1}^{m} x_{ij}^{2}\right)^{\frac{1}{2}}} \; . \tag{6}$$

This being done, the virtual best A$^+$ and worst A$^-$ alternatives are determined using the $x_{ij}{}^*$. The best alternative consists of all the best values from the normalised decision matrix for each criterion and the worst alternative accordingly. For each alternative $i = 1, \dots, m$ the Euclidean distance to these virtual alternatives is calculated as a measure of the position to the best and the worst value, S_i^+ and S_i^-. Eventually, these measures are aggregated to one measure of relative closeness:

$$C_i = \frac{S_i^-}{S_i^- + S_i^+} \text{ , } for\ i = 1, \dots, m \,. \tag{7}$$

This measure will be in the interval [0; 1] and a higher value indicates a better performance of the alternative.

2.2.3 Evaluation Based on Distance from Average Solution

The EDAS approach was developed by Keshavarz Ghorabaee et al. [10] and has a similar structure as the TOPSIS method since it also relies on distance measures but in this case the distance to an average alternative. Equivalent to how it is done in the TOPSIS method, the decision matrix with all values x_{ij} of all $i = 1, \dots, m$ alternatives for each criterion $j = 1, \dots, n$ has to be built. However, a normalisation of the decision matrix is not necessary in this case.

In a first step, the average solution is calculated by taking the mean of all values per criterion:

$$AV = \left\{ \left(\frac{1}{m} \sum_{i=1}^{m} x_{ij} \right) \right\} = \{AV_1, \dots, AV_n\} \text{ , } for\ j = 1, \dots n \,. \tag{8}$$

Furthermore, the positive and negative distances to the average solution AV are computed. A positive distance is added to the sum of positive distances, SP_i, if the value of an alternative x_{ij} performes better than the average solution AV_j for the criterion *j*. Accordingly, the sum of negative distances, SN_i, is fed by values that perform worse than the average solution. The criteria weights, w_j, are included when aggregating all the positive, and negative respectively, distances.

The final performance score for each alternative $i = 1, \dots, m$ is obtained by taking the mean of the two normalised weighted aggregated distances:

$$A_i = \frac{1}{2} \left(\frac{SP_i}{\max\limits_i SP_i} + \left(1 - \frac{SN_i}{\max\limits_i SN_i} \right) \right). \tag{9}$$

The ranked alternatives will always lie in the interval [0; 1] while the best ranked alternative will meet the value 1 and the worst ranked alternative will have the value 0.

3 Case Study

The methodology is applied to different energy systems for a typical multi-family house in Düsseldorf, Germany.

3.1 Building energy profiles

The building is assumed to include eight flats of each 70 m^2 with a space heating demand of 100 kWh/m^2 which corresponds to an unrenovated building from the 1970s [11, 12, 13, 14]. An additional hot water demand of 700 kWh/person [15] is multiplied by the mean number of people per household of 1.7 people for a building of such a kind [11, 12]. The regarded building type therefore has a total of 56,000 kWh annual space heating demand and 9,520 kWh annual hot water demand.

Synthetic load profiles for space heating and hot water demand were simulated following VDI 4655 [16]. The norm provides reference load profiles of both heating and hot water in existing multi-family houses for ten categories of typical days. These categories are dependent on the seven-day-rolling-average of the ambient temperature, the cloudiness, and the day of the week. Moreover, location information is used to multiply the reference profiles by a correction factor. Through the algorithm provided in the norm, the annual demand is distributed over the year accordingly.

3.2 Scenario input data

Further input data of the optimisation problem, like weather, energy prices and energy emissions are given in Table 2. It is distinguished between the two considered scenarios – the year 2021 and November 2022. The prices and emission data are taken from publicly available databases and the weather data is taken from the test reference year data set for Düsseldorf from Deutscher Wetterdienst [17]. The price data corresponds to household tariffs for the respective energy form.

Table 2: Input data for the two regarded scenarios

Data type	Scenario 2021	Scenario 2022
Weather data	DWD-TRY 2017, Düsseldorf	DWD-TRY 2017, Düsseldorf
Electricity price [€ / kWh]	0.337 [18, 19]	0.482 [20]
Gas price [€ / kWh]	0.083 [21, 22]	0.163 [21, 22]
Pellet price [€ / kWh]	0.048 [23]	0.149 [23]
Electricity grid emission factor [kg CO_2 / kWh]	0.420 [24]	0.420 [24]
Gas emission factor [kg CO_2 / kWh]	0.201 [25]	0.201 [25]
Pellet emission factor [kg CO_2 / kWh]	0.022 [26]	0.022 [26]

3.3 Energy systems

We regard four different energy systems which meet the space heating and hot water supply for the described building type. The systems comprise of a fixed composition of energy technologies. It is distinguished between technologies that are assumed to be already installed (existing) in the building and newly added technologies to transform the system. System 1 (S1) consists of an air-water heat pump, an existing gas boiler and a thermal storage. System 2 (S2) consists of an air-water heat pump, a solar thermal collector and a thermal storage. System 3 (S3) consists of an existing gas boiler, a solar thermal collector and a thermal storage. System 4 (S4) consists of a pellet boiler, a solar thermal collector and a thermal storage. The energy flows, which show how the energy is transformed and passed in the system are shown in Figure 2. As can be seen in the graphs, the energy produced by the system's components can either be used directly for fulfilling the demands or it can be intermediately stored in a thermal storage.

The existing gas boilers have a fixed maximum power output dependent on the maximal demand from the space heating and hot water load profiles:

$$P_{gas\ boiler}[kW] = 1.25 * (P_{max,space\ heating}[kW] + P_{max,hot\ water}[kW])\,. \quad (10)$$

Investment costs for the gas boiler are not regarded in the optimisations of S1 and S3.

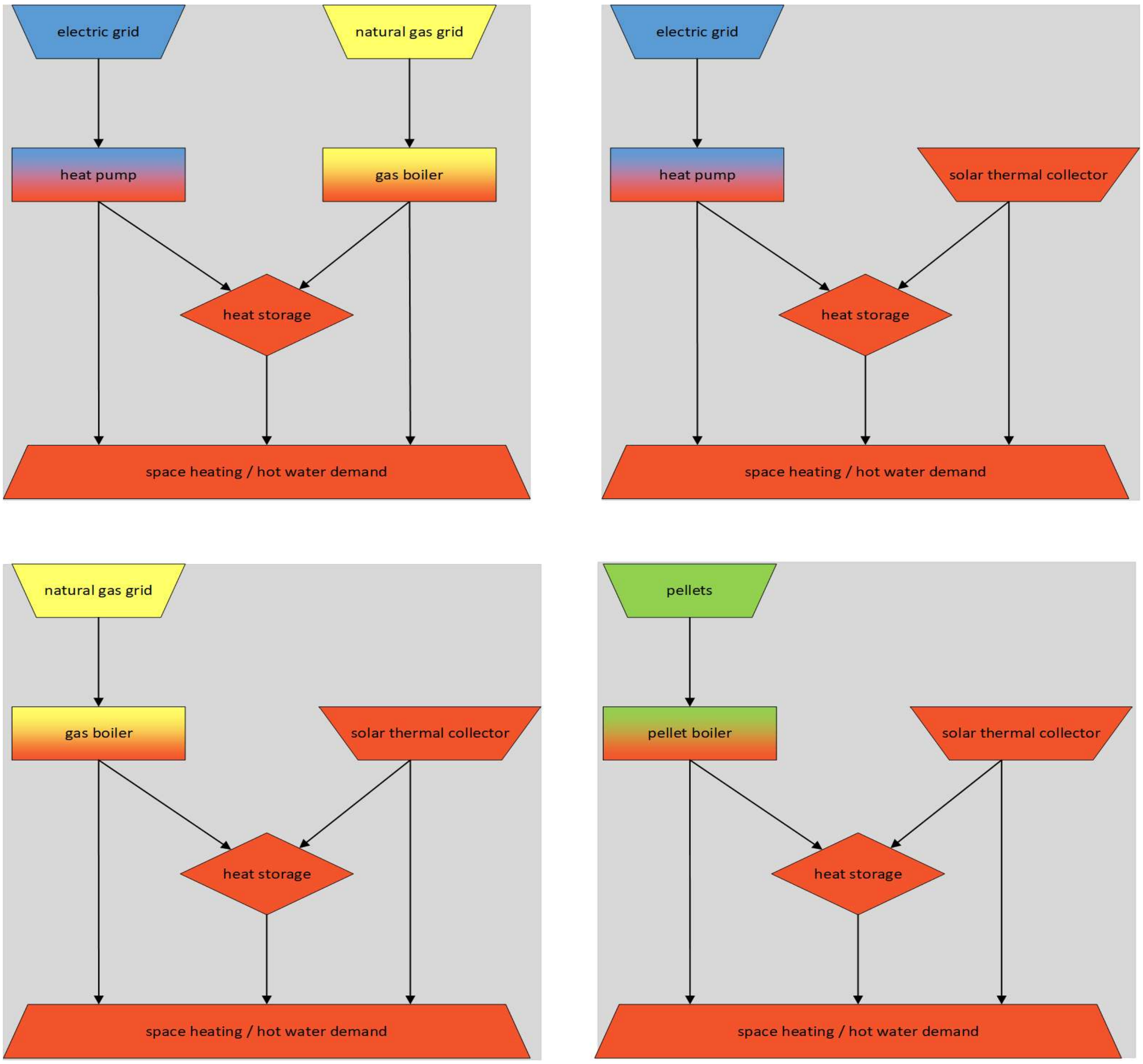

Figure 2: Energy flow graphs of the modelled energy systems. Upper left graph depicts S1, upper right S2, lower left S3 and lower right S4. The colour scheme indicates the respective energy sector: blue is the electricity sector, red the heat sector, yellow the gas sector and green the biomass sector.

4 Results

After having introduced the methodology and case study, the results of the criteria weight determination, the energy system optimisation and the multi-criteria analysis are presented.

4.1 Energy system optimisation

All four heat concepts were optimised with single-objective optimisation and with multi-objective optimisation for the scenarios 2021 and 2022. To analyse the impact of the multi-objective optimisation we calculate the marginal costs of reducing the CO_2 emissions by 10 %. Since the emissions and the costs are competing criteria in all regarded systems, the limitation of emissions always comes with an increase in costs.

We find that a reduction of CO_2 emissions by 10 % leads to a cost increase of 7-51 % in 2021. For 2022, the cost increase is only 4-23 %. However due to the increasing energy prices, the systems' total annual costs without emission constraint have already increased by on average 80 % within one year.

The highest marginal costs are observed for S4 and the lowest for S1. This can be explained by the fact that S4 is the least reliant on grid-induced CO_2 emissions while S1 is the most reliant on them. Therefore, the CO_2 limitation on S4 leads to a bigger layout of the solar thermal collector and the heat storage which comes with a high increase in investment costs whereas in S1, the CO_2 limitation leads to a higher share of the heat pump in the heat supply of the system, and this is accompanied by a high efficiency so that the costs only increase slightly for the limitation on the CO_2 emissions.

The highest increase of the total annual costs is observed for S4 because the relative increase of the pellet price per kWh is the highest of all considered energy types. However, this system has by far the lowest emission results of all four regarded systems. All results for the emissions and costs of each alternative are summed up in Figure 3.

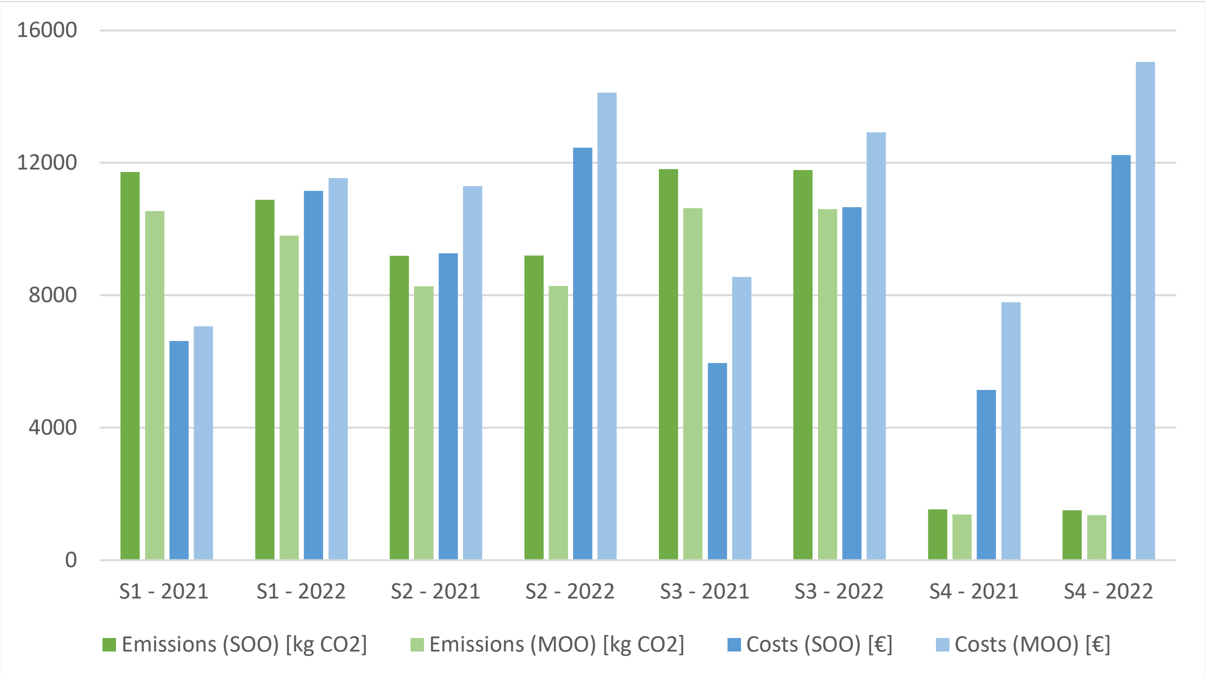

Figure 3: Overview of the optimisation for the different energy systems and scenarios

The change in optimisation method always influences the layout of the built energy system components and the operation of them. The most significant difference in the results between the optimisation methods can be seen in the built size of the solar thermal collector. Under the CO_2 constraint, the collector area is more than eight times bigger in each of the regarded systems that include a solar thermal collector.

Furthermore, a change in the grid-independence and the self-sufficiency is observed. The grid-independence is a metric for the relative amount of energy produced within the system boundaries (independent from a grid-connection) and used for the demands from all the energy in the system which is used for the fulfilling of demands. A value of 0 indicates a complete dependence on gas and/or electricity grids while a value of 1 indicates a full independence from these grids. The self-sufficiency gives the ratio of energy produced within the system boundaries and used in it from all the energy produced within the system boundaries. A value of 0 indicates no use of the energy produced within the system boundaries for the system, while a value of 1 indicates full use of the energy produced within the system boundaries for the system. For the given study we find that the grid-independence rises by a factor of around five for S2, S3 and S4 when the CO_2 limitation is added (S1 is either way fully grid-dependent). The self-sufficiency, however, decreases in the event of CO_2 limitation because of the oversized solar thermal collector and the additional losses to the environment for the situation when the demand is significantly lower than the collector's output.

4.2 Criteria weights

The two criteria weights have been determined according to the AHP method (Chapter 2.2.1). The pairwise comparison of the criteria was performed through a survey in which employees of a local utility company participated. The survey contained a pairwise comparison of economic, environmental and technological criteria. In total, eleven employees of the local utility company filled out the survey and each resulting set of criteria weights was determined using the AHP method and then averaged. In this study we only regard economic and environmental criteria to concentrate on the same criteria which have been used in the optimisation methodology. The final set of criteria weights resulted in

- economic: 0.53,
- environmental: 0.47,

which were used as default weights in the application of all three assessment methods. According to Cinelli et al. [27], the AHP weights should only be used with the same method. However, TOPSIS and EDAS do not include a method to determine criteria weights and using the AHP weights for these methods can be seen critical. Therefore, for analysing the results of the TOPSIS and EDAS method, it should be considered that the weights were obtained with a method which might be unsuited.

4.3 Multi-criteria analysis of the optimisation results

The ranking assessment according to all three methods that were introduced in Chapter 2.2 is performed. The ranking results from each method and an additional average ranking are displayed in Figure 4. All systems including the scenario and objective variants are ranked among each other. This yields a total of sixteen alternatives. The comparison of the graphs shows the difference in the cardinal scales from the ranking results from each of the methods. The average ranking has a somewhat intermediate scale since it was obtained by averaging the score values of each method for each alternative. Evidently, the best rated system for both prices scenarios and optimisation variants is the system with the pellet boiler (S4). For S4 at least three out of four alternatives are among the best rated. Moreover, it is evident that the score of the best four/two/three alternatives (of the AHP/TOPSIS/EDAS ranking) is significantly higher than the scores of the other alternatives. Overall, the alternatives of the 2021 scenario perform better than the results from the 2022 scenario which is traced back to the high increase in costs. However, S4 remains to be the system with the highest score even under the cost increase.

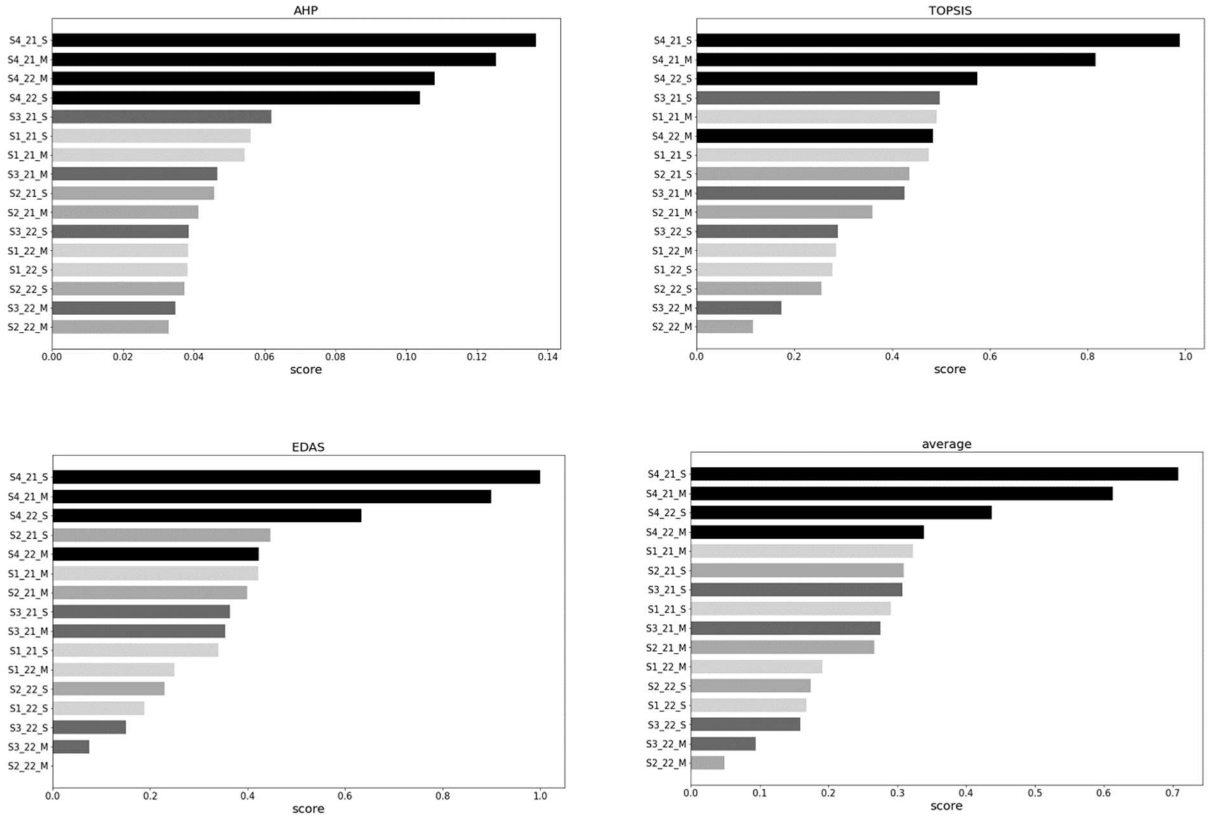

Figure 4: Results of the aggregated ranking for all calculated heating systems in all scenarios. The score can lie between 0 and 1. The bars are named after the energy system and the scenario year, and it is indicated if the objective function used a single criterion (S) or additionally the direct CO_2 emissions (M). The colour scheme is geared to the energy system.

4.3.1 Sensitivity analysis of the chosen MCDA method

In order to better illustrate how the ranking positions of each system alternative change for a different method choice, the ranking position per alternative and method is shown in Figure 5. The ranking position of the two best and the two worst alternatives do not change under different methods. As it was already derived from Figure 4, S4 in the 2021 scenario and for both objective variants is the best system and robust against the choice of the MCDA method under the given criteria weight. S4 with a single cost objective would be the best system choice for the 2022 scenario. Figure 5 furthermore shows that there is only little change in the ranking positions between the AHP and TOPSIS method. However, there is a significant change in ranking positions between TOPSIS and EDAS and thus also between AHP and EDAS. In the average ranking these differentiations are to a certain extent balanced out, but the average ranking still comprises a bias because of the various cardinal scales for the scores obtained by the different methods.

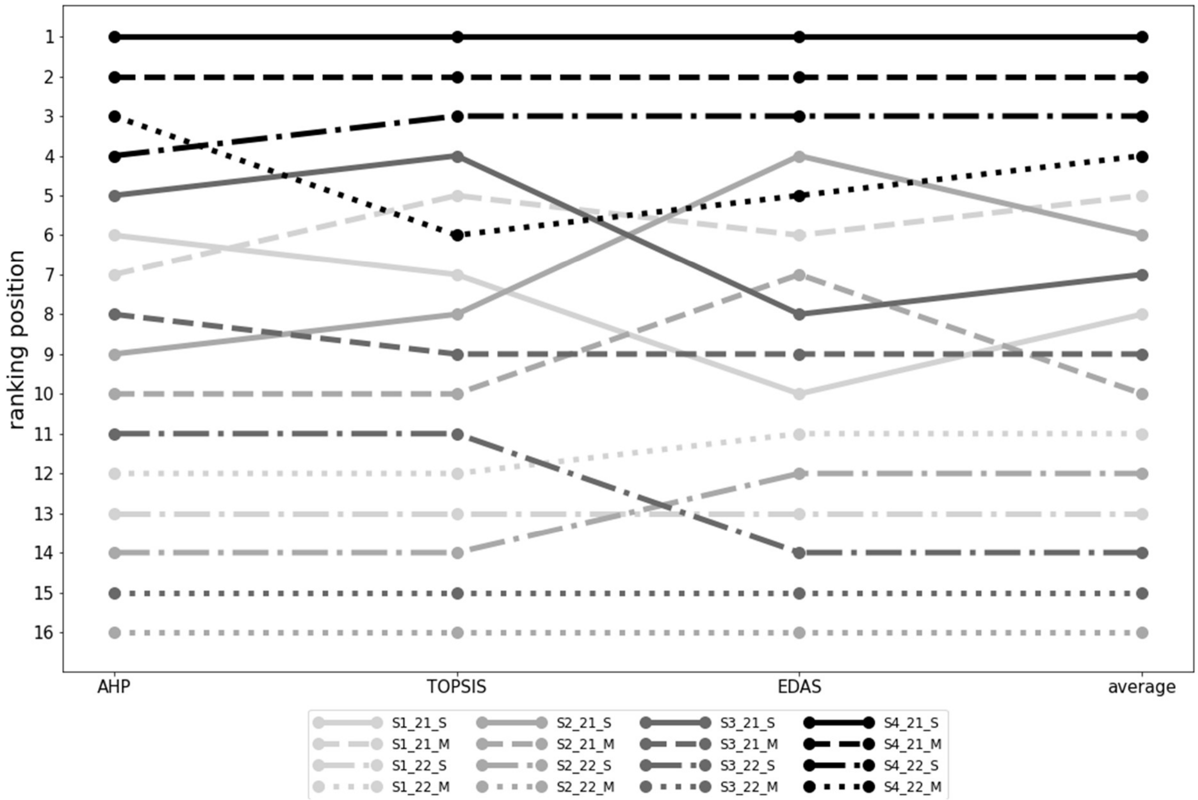

Figure 5: Ranking position of the system alternatives for the different methods and the average ranking.

The changes in ranking position were further investigated. Hence, a metric for the total deviation of the alternatives' ranking positions in each method to the alternatives' ranking positions in the average ranking was derived. In this metric, given in Eq. (11), all the deviations in position are summed up over all the alternatives.

$$DEV_{method} = \sum_{alternatives} |POS_{method} - POS_{average}| \tag{11}$$

For the given study we find $DEV_{AHP} = 18$, $DEV_{TOPSIS} = 14$ and $DEV_{EDAS} = 10$.

4.3.2 Sensitivity analysis of the criteria weights

We further investigate the impact of the criteria weights on the ranking results. This analysis is performed only on the AHP ranking since the weights were obtained with the AHP method and the AHP ranking therefore has the highest credibility regarding the use of the weights. Since there are only two criteria whose weights must add up to 1, changing one of the criteria weights unambiguously determines the other weight. We decide to vary the economic weight between [0, 0.2, 0.4, 0.53, 0.6, 0.8, 1]. Recall that the value 0.53 was obtained from the utility company survey and is therefore the reference point for the AHP ranking as how it is presented in Chapter 4.3.

The results of the sensitivity analysis are shown in Figure 6. For an economic weight in the interval [0, 0.6], all alternatives for system S4 share the first four positions in the ranking. This implies that S4 is also highly robust against changes of the criteria weights. Remarkable is that for all $w_{economic} < 0.4$, the multi-objective approach for S4 is most beneficial but for all other weights S4 in the 2021 scenario with a single objective performs best. For a high weight on the economic criterion, the other three systems get higher AHP ranking scores. Overall, the scores are closer together in quantitative terms for a high economic weight and the spread between the performance of S4 and the others is more extreme with a low economic weight. This can be explained due to the good performance of S4 in the environmental criterion because of the high renewable energy share in this system.

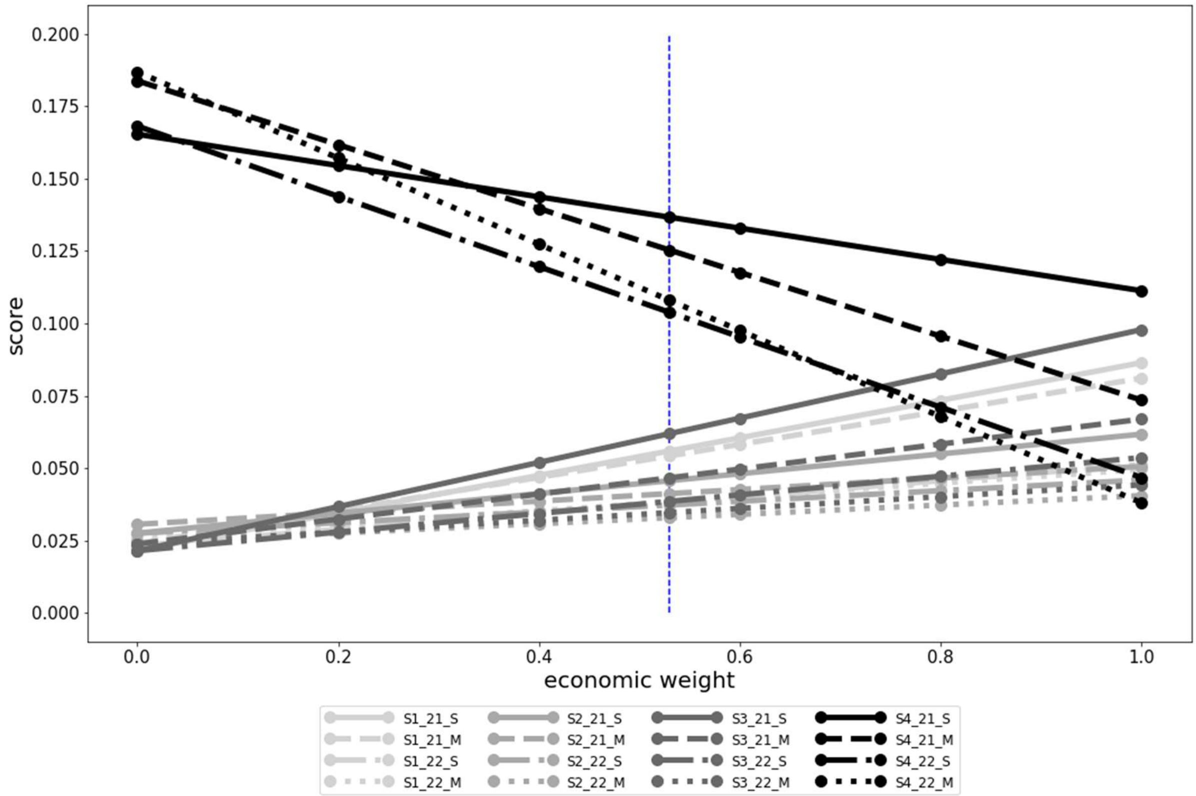

Figure 6: Sensitivity analysis of the economic criteria weight on the AHP score for the alternatives. A vertical line is set at the position of the reference ranking with the criteria weights from the survey.

5 Discussion and Conclusion

Under the effect of increasing energy prices, we analysed the environomic performance of four different building heat systems. The optimisation model included the inspection of multi-objective optimisation and has been applied to a typical unrenovated multi-family house in Düsseldorf, Germany.

We find that the total annual system costs increased by on average 80 % due to the increasing energy prices. The marginal costs of 10 % CO_2 emissions saving range from 4 % for S1 in 2022 to up to 51 % for S4 in 2021. Besides, the consideration of two objectives changes the size of the technology components and the operation of the energy systems. The major effect is the oversizing of the solar thermal collector which increases the grid-independence.

The optimisation results have been ranked according to three different MCDA methods: AHP, TOPSIS and EDAS. The chosen criteria for this analysis are environmental and economic criteria, even though more criteria categories such as technological criteria could have been added. The MCDA results show that even under increased energy prices, S4 has a higher score than the other systems at lower energy prices. In fact, S4 is the most robust to the price increase under cost and emission criteria.

We find that different MCDA methods lead to a different ranking of the alternatives. In the given study, however, the best performing alternative is robust over all different methods and the same holds for the worst performing alternative. As introduced in Chapter 2.2, the three methods all give a final score to each alternative. However, the cardinal scales differ between the methods. We perform an average ranking over all three methods which breaks the cardinal scales in which the alternatives' scores lie. The effect of an average ranking was analysed by introducing a new metric DEV_{metho} for the deviations of the alternatives in each method to the average ranking. This metric shows the highest deviations for the AHP ranking to the average ranking which can be explained by the difference in the scales. The scale of the performance scores from the AHP method is significantly different to the scales from the TOPSIS and EDAS methods. The average ranking should therefore be used precautiously.

A sensitivity analysis of the criteria weights in the AHP method shows that S4 performs best over a wide range of the choice of criteria weights. Only for a significant weight on the economic criterion, all alternatives have a shorter value range in AHP scores and the dominance of S4 is eliminated.

To conclude, with this study we give an overview on how the increasing energy prices affect different, specific building heat systems. We consider economic and environmental criteria and perform multi-criteria analysis based on optimisation results for each system. Based on these results, utilities can adapt their product strategies.

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Literature

[1] Deutscher Bundestag, October 12th, 2022, *Sachverständige: Wir müssen um jedes Zehntelgrad weniger Erderwärmung kämpfen*, In: text archive.

[2] Krien et al., 2020, *oemof.solph—A model generator for linear and mixed-integer linear optimisation of energy systems,* In: Software Impacts, Volume 6, p. 100028, Available from: doi: 10.1016/j.simpa.2020.100028.

[3] Gurobi optimization, LLC, 2022, https://www.gurobi.com/.

[4] Stein et al., 2016, *PVLIB: Open Source Photovoltaic Performance Modeling Functions for Matlab and Python*, In: IEEE 43rd Photovoltaic Specialists Conference.

[5] Ishizaka et al., 2013, *Multi-criteria decision analysis: Methods and software*, In: Chichester West Sussex United Kingdom: Wiley. ISBN: 9781119974079.

[6] Lazaroiu and Ciupageanu, 2019, *Multi-criteria decision making in sustainable renewable energy systems*, In: 19th International Multidisciplinary Scientific GeoConference Proceedings, Volume 19, Issue4.1, Part A, Available from: doi: 10.5593/sgem2019/4.1/S17.042.

[7] Saaty, 1987, *The analytic hierarchy process: what it is and how it is used,* In: Mathematical Modelling, Volume 9, no. 3-5, pp. 161-176, Available from: doi: 10.1016/0270-0255(87)90473-8.

[8] Zhang et al., 2019, *Probabilistic multicriteria assessment of renewable micro-generation technologies in households,* In: Journal of Cleaner Production, Volume 212, p. 582.

[9] Hwang and Yoon, 1981, *Methods for Multiple Attribute Decision Making*. In: Hwang, Yoon (eds.). Multiple Attribute Decision Making. Berlin and Heidelberg: Springer, pp. 58-191. Lecture Notes in Economics and Mathematical Systems. ISBN: 978-3-642-48318-9. Available from: doi: 10.1007/978-3-642-48318-9_3.

[10] Kesharvarz Ghorabaee et al., 2015. *Multi-Criteria Inventory Classification Using a New Method of Evaluation Based on Distance from Average Solution (EDAS)*, In: Informatica, Volume 26, no. 3, pp. 435-451.

[11] Statistische Ämter des Bundes und der Länder, 2011, *Zensus 2011, Düsseldorf: Gebäude und Wohnungen*.

[12] Landeshauptstadt Düsseldorf - Amt für Statistik und Wahlen, 2016, *Wohnen in Düsseldorf und Situationen von Menschen mit einer Wohnproblematik*.

[13] Statistisches Bundesamt, 2020, *Bautätigkeit und Wohnungen: Bestand an Wohnungen*.

[14] Umweltamt Landeshauptstadt Düsseldorf, 2010, *Hausdatenblätter der Gebäudetypologie,* Available from: https://www.duesseldorf.de/saga/sanierung/gebaeudetypologie.html (Access on October 7th, 2022).

[15] Selectra SAS, *Energieverbrauch Warmwasser: Mit 7 praktischen Tipps sparen!,* Available from: https://energiemarie.de/energietipps/wissenswert/energieverbrauch/warmwasser (Access on October 7th, 2022).

[16] V. e. V, 2021, *VDI-Richtlinie 4655*.

[17] DWD, *Testreferenzjahre (TRY).* Available from: https://www.dwd.de/DE/leistungen/testreferenzjahre/testreferenzjahre.html (Access on January 24th, 2023).

[18] FfE München, *Deutsche Strompreise an der Börse EPEX Spot in 2021,* Available from: https://www.ffe.de/veroeffentlichungen/deutsche-strompreise-an-der-boerse-epex-spot-in-2021/ (Access on June 2nd, 2023).

[19] Boston Consulting Group, 2021, *Klimapfade 2.0: Ein Wirtschaftsprogramm für Klima und Zukunft*.

[20] Verivox, *Verbraucheratlas*, Available from: https://www.verivox.de/strom/verbraucheratlas/strompreise-deutschland/ (Access on November 3rd, 2023).

[21] Investing.com, Dutch TTF Natural Gas Futures Historische Preise, Available from: https://de.investing.com/commodities/dutch-ttf-gas-c1-futures-historical-data (Access on June 2nd, 2023).

[22] Bdew, *BDEW-Gaspreisanalyse April 2023,* Available from: https://www.bdew.de/service/daten-und-grafiken/bdew-gaspreisanalyse/ (Access on June 3rd, 2023).

[23] ÖkoFEN Forschungs- und Entwicklungs Ges.m.b.H, *Pellets Preis Juni 2020 | Aktuelle Pelletspreise - ÖkoFEN*, Available from: https://www.oekofen.com/de-de/aktueller-pelletspreis/ (Access on June 2nd, 2022).

[24] Umweltbundesamt, *Strom- und Wärmeversorgung in Zahlen,* Available from: https://www.umweltbundesamt.de/themen/klima-energie/energieversorgung/strom-waermeversorgung-in-zahlen#Strommix (Access on June 2nd, 2022).

[25] Umweltbundesamt, Ed., *CO2-Emissionsfaktoren für fossile Brennstoffe*, In: Dessau-Roßlau, Climate Change 27/2016, Available from: https://www.umweltbundesamt.de/sites/default/files/medien/1968/publikationen/co2-emissionsfaktoren_fur_fossile_brennstoffe_korrektur.pdf (Access on June 2nd, 2022).

[26] Deutsches Pelletinstitut, *Klima und Umwelt*, Available from: https://www.depi.de/klima-und-umwelt (Access on January 24th, 2023)

[27] Cinelli et al., 2022, *Proper and improper uses of MCDA methods in energy systems analysis*, In: Decision Support Systems. Vol. 163, p. 113848, Available from: doi: 10.1016/j.dss.2022.113848.