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# Robust bioenergy technologies for the German heat transition: A novel approach combining optimization modeling with Sobol' sensitivity analysis

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**Abstract**

Uncertainties are one of the major challenges of energy system optimization models (ESOM), yet little use is made of systematic uncertainty assessments in ESOM-based analyses. In this paper, an ESOM is combined with the global sensitivity analysis of Sobol' to identify robust, competitive bioenergy technologies to fulfill the climate targets in the German heat sector under uncertain developments. Through the outlined method, only three out of 32 investigated parameters were identified to have uncertainties with significant impacts on the future competitiveness of bioenergy technologies: the power price, gas price and the defined climate target. Based on these findings, a solution space is quantified showing which bioenergy technologies are robust, competitive options under the uncertainty of the three influencing parameters. The use of biomass in the form of wood chips in (high temperature) industry applications is found to be the most robust choice in all cases, while hybrid combined heat and power wood pellet systems are an additional robust option when future power prices are increasing. Both technologies have the potential to close gaps in a sustainable energy system and should be considered for the future use of biomass in the German heat sector, when designing policies.

*Keywords:* heat sector, bioenergy, optimization, sensitivity analysis, Sobol'

## 1. Introduction

Climate change requires a transition of national energy systems away from fossil fuels to renewable solutions. In the case of Germany, emissions are to be reduced by 80-95% compared to 1990. A major share of that reduction needs to be covered by renewable heat solutions, which provided only 14% of the German heat demand in 2018 [18]. Bioenergy was the largest renewable heat contributor, but its potential is limited and its future use is uncertain. Therefore, insights need to be generated that inform policy makers about the cost-optimal use of bioenergy in a sustainable German heat sector under uncertain developments.

To determine possible least cost system pathways towards a renewable energy supply, ESOMs are widely used. Calculated model results are diverse and often lead to different recommendations. A major criticism of this approach is that the models are shaped by factors which are deeply uncertain [20], including e.g. technology innovation, resource availability, future feedstock price developments and socio-economic dynamics. Similar uncertainties arise in the German energy or heat sector and need to be considered when applying ESOMs to inform policy makers. Accordingly, possible methods that can address these issues need to be evaluated.

Two types of uncertainties can be distinguished for ESOMs [33]: parametric and structural. Parametric uncertainty refers to imperfect knowledge of ESOM input values. Structural uncertainty refers to the imperfect mathematical relationships within the model. To address these limitations, uncertainty assessments

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can be applied. Yue et al. [50] outline a review of approaches to uncertainty assessment in ESOMs. The majority of over 2000 studies associated with ESOMs have been used in a deterministic fashion with limited attention paid to uncertainty. About 100 studies used a scenario analysis to address uncertainty and only 34 studies performed a systematic uncertainty assessment. Scenario analysis is one of the simplest ways to explore the decision landscape under alternative futures. It has been criticized, e.g. as "black-box" due to its lack of transparency [14], as a deterministic methodology not suitable for complex problems with inherent uncertainties [47] and as a method that underestimates the range of possible outcomes [32]. Within best practice formulations for ESOMs, DeCarolis et al. [20] recommends performing a systematic uncertainty assessment to quantify uncertainty wherever possible. A systematic assessment can test the robustness of the model results by identifying which parameters drive the model outputs and help focus scenario analyses [20]. Today only a few studies follow these recommendations [28, 29, 31, 38].

Yue et al. [50] identified four prevailing approaches that have been applied to systematically assess uncertainty in ESOMs: Monte Carlo analysis (9 findings), stochastic programming (18), robust optimization (3), and modeling to generate alternatives (4). Each of the four techniques has its own focus, advantages and limitations. In principle, Monte Carlo analysis varies the uncertain input parameters over a probability distribution. The resulting collection of model outputs can then be evaluated statistically using a global sensitivity analysis. The combination of Monte Carlo and global sensitivity analysis can address both parametric and structural uncertainty. It is a powerful technique compared to the other approaches addressing uncertainty, but it suffers heavily from computational burden. It requires hundreds to thousands of model evaluations, making it impractical for complex models with a long model run time. However, DeCarolis et al. [20] recommends applying Monte Carlo/ global sensitivity analysis, as a best practice wherever possible to test the robustness of model results and insights.

Variance-based, global sensitivity analyses, also known as Sobol' methods, are versatile. They are well suited for taking input factor interactions into account and have established themselves among practitioners in many scientific fields [42, 44, 49]. However, to the authors' knowledge, it has not yet been applied to ESOMs. The only similar approach applies the Morris screening method on energy models, which performs local sensitivity analyses in a global context, and is computationally less demanding [29, 38]. In this study, a method is performed to identify uncertainties in ESOM results by combining optimization modeling with the global, variance-based sensitivity analysis of Sobol'. The majority of parameters, all having uncertainties within their future development, are investigated. The effect of each parameter and its interaction with the other parameters on the model outcome is determined. Based on the identified, significantly influential input parameters, a solution space for technology competitiveness is generated. This approach is computationally expensive, but purposeful when aiming to quantify uncertainty. As mentioned above, limited attention is paid to uncertainty in ESOMs and a need for practical methods to quantify uncertainty exists. The method in this paper can serve as a case study for ESOM's with a model run time in the range of minutes and can theoretically be applied to any ESOM or region.

In this case, the outlined method is applied to a model optimizing the future use of biomass in the German heat sector [23, 24]. In former studies, various scenarios were calculated with this model to identify competitive bioenergy technologies in a future heat sector, fulfilling the climate targets. The chosen model is set up with a high level of detail in regard to technical and economic input data, but is still well suited for a quantitative sensitivity analysis, as the model run time is in the range of one minute, which is crucial to perform a quantitative sensitivity analysis [41].

Biomass has advantageous properties compared to other renewable resources, such as weather independency, simple storage and flexible utilization, which open up a wide field of applications for biomass. However, biomass is limited and its future use in order to fulfill the greenhouse gas (GHG) reduction targets in the German heat sector is uncertain and to be investigated in this paper by assessing the following research questions: Which bioenergy technology concepts are robust, cost-competitive solutions for fulfilling the climate targets in a future German heat sector? Which factors are significantly influential for the cost competitive future use of bioenergy? In this study, a comprehensive sensitivity analysis and thereby a quantifiable solution space for the future role of biomass in the German heat sector is identified in order to improve the robustness of the outputs from optimization modeling and their use in providing policy insights.

## 2. Materials and method

### 2.1. The optimization model

The optimization model was used in former research to determine the future, cost optimal use of biomass in the German heat sector under different long term climate mitigation scenarios [23, 24]. In this study, the same model formulations are used, but all input parameters are not set according to a certain scenario. Instead, a probability distribution of the parameter uncertainties is systematically assessed.

The model structure is as follows: The three main sectors of the German heat sector, private household, industry and trade/ commerce are further divided into several sub-sectors, with different properties in terms of demand profiles and infrastructures. In total, 19 sub-sectors were defined and described. The future development of the heat demand in each sub-sector is based on the external results of the building stock model 'B-STar' [25], which models the future refurbishment of the German building stock in a yearly resolution using an agent based approach. Within the optimization model, for each sub-sector, representative bioenergy-, fossil- and other renewable (hybrid-) heat technology concepts are described [27], incl. e.g. gas boiler, heat pumps, direct electric heating, solar thermal, log wood, wood pellet and wood chip technologies. Possible feedstocks for each technology are defined. In total 20 biomass products (incl. wood based residues, log wood, straw, manure, two perennial crops and seven types of energy crops) and 3 fossil feedstocks are possible inputs, see supplementary data [27]. For the single technology components, infrastructure emissions as well as the feedstock specific emissions are considered within the model.

The technological choice is optimized between 2015 - 2050 in a yearly resolution, while fulfilling the German climate mitigation targets [16, 17]. The objective function is minimizing the total system costs over all technologies, sub-sectors and the complete time span, using the Cplex solver for the linear problem. The spatial boundary is Germany as a whole and the sectoral coverage exclusively includes the heating sector. A consistent framework was set up representing the linkage to the power sector. For a detailed description of the model formulations, the linkage to the power sector, the definition of the sub-sectors and technology concepts as well as the possible feedstock and technology pathways the reader is referred to [24]. Detailed economic and technical data of the technology concepts can be found in supplementary data [27].

### 2.2. Assessment of parameter uncertainty

From the input data of the optimization model, parameters with a possible uncertainty in their future development were selected for the uncertainty assessment. The choice whether a parameter is attached with a future uncertainty was based on expert elicitation. Table 1 shows the selected 32 parameters and the range in which the parameters were varied for the sensitivity analysis. Information on the uncertainty range of the parameters was obtained through existing studies or expert elicitation.

In seven cases, parameter values are not static, but dynamically changing over time and their uncertainty is increasing with progressing time, as e.g. in future feedstock price developments. Fig. 1 exemplarily shows the development of the future electricity-only market price according to 12 different scenario studies. The investigated uncertainty range of the power price development in this study (grey area) is determined by calculating the mean of the 12 scenarios ± the corresponding empirical standard deviation. Within this uncertainty range (grey area), price development curves are sampled and assessed within the sensitivity analysis. The uncertainty range of the other parameters dynamically changing over time is determined using the same method.

Apart from the 32 parameters in Table 1, future uncertainty is also attached to the heat demand development and depends on the refurbishment rate of the different sub-sectors. The data used for the heat demand development in the optimization model is adopted from an external source and only available for an 80% and 95% GHG reduction scenario [25]. Consequently, it is not purposeful to sample curves within an uncertainty range. Instead, the heat demand development is linked to the GHG reduction target. In cases of $80 - 87.5\%$ GHG reduction in 2050, the heat demand development data set of the 80% scenario is adopted. For higher GHG reductions in 2050, the data set of the 95% scenario is applied.

The future availability of biomass in general and particularly for heating purposes also has uncertainty. In the DBFZ resource data base [10] current biomass usage and unexploited potential from residues is investigated for over 80 types of residues. Within this data base, maximal and minimal values for every

Table 1: Assessed input parameters and their defined uncertainty range. A variation of +/- is compared to the initial value in Jordan et al. [24]. The heat demand development is adopted from an external source [25] and linked to the GHG reduction target. PMEF = power mix emission factor

| **Parameter range** | **Min in %** | **Max in %** | **Source** |
|---|---|---|---|
| Power price in €/MWh | 32.0 → 43.5 | 32.0 → 165.6 | [2, 5–7, 11, 25, 39, 43] |
| Gas price in €/MWh | 19.8 → 24.6 | 19.8 → 42.6 | [4, 5, 7, 9, 25, 35, 36, 39, 43] |
| Coal price in €/MWh | 9.4 → 9.0 | 13.3 → 23.3 | [4, 5, 7, 25, 35, 36, 39, 43] |
| $CO_2$ cert. price in €/t$CO_2$equiv. | 10.9 → 17.8 | 17.7 → 286.5 | [1, 3–5, 7, 9, 25, 35, 36, 39, 43] |
| PMEF in g$CO_2$equiv./kWh | 564.8 → 12.7 | 585.9 → 96.5 | [8, 25, 34, 35, 37, 39, 43] |
| Increase of biomass prices in %/a | 1 | 5 | Derived from historical data |
| Discount rate | 1 | 7 | Steinbach and Staniaszek [45] |
| GHG reduction target | 80 | 95 | 'Energiekonzept' [17] |
| Biomass potential | see 2.2 | see 2.2 | DBFZ - Data repository [10] |
| Bio. potential pre-allocated to heat | act. use → 30 | act. use → 70 | Derived from Szarka et al. [46] |
| Yield energy crops combustion | -33 | +33 | Derived from KTBL [26] |
| Yield energy crops digestion | -20 | +20 | Derived from KTBL [26] |
| Emission factors biomass feedstocks | -30 | +30 | |
| Emission factors fossil feedstocks | -10 | +10 | |
| Investment wood chip tech. | -10 | +10 | |
| Investment wood pellet tech. | -10 | +10 | |
| Investment log wood tech. | -10 | +10 | |
| Investment electric heating | -10 | +10 | |
| Investment heat pump tech. | -10 | +10 | |
| Investment solar thermal tech. | -10 | +10 | |
| Investment gas tech. | -10 | +10 | |
| Lifetime wood chip tech. | -5 | +5 | Expert elicitation |
| Lifetime wood pellet tech. | -5 | +5 | |
| Lifetime log wood tech. | -5 | +5 | |
| Lifetime electric heating | -5 | +5 | |
| Lifetime heat pump tech. | -5 | +5 | |
| Lifetime solar thermal tech. | -5 | +5 | |
| Lifetime gas tech. | -5 | +5 | |
| Conversion efficiency wood chip tech. | -5 | +10 | |
| Conversion efficiency wood pellet tech. | -5 | +10 | |
| Conversion efficiency log wood tech. | -5 | +10 | |
| Conversion efficiency biogas | -5 | +10 | |

type of residue is defined, based on a consistent comparison of existing findings from literature [15]. This data, combined with energy conversion factors [12, 13] and the yearly available potential of log wood [21], serve as a basis for our investigation. The uncertainty span for the available biomass potential from energy crops is sampled along a defined range (2.4 mio ha in 2015; 0 - 2 mio ha in 2050). From this potential, a certain share of the available biomass potential is pre-allocated to the heat sector. This pre-allocation is deeply uncertain and sampled along a range, starting with the actual amount of biomass used for heat in 2015 towards 30-70% of the available potential in 2050. This range is derived from the review by Szarka et al. [46], which shows the projected spread of future biomass usage over the German energy sectors in various energy scenarios. The uncertainty of the biomass potential and the biomass potential pre-allocated for heating purposes is analyzed as a whole and not separately for each biomass product.

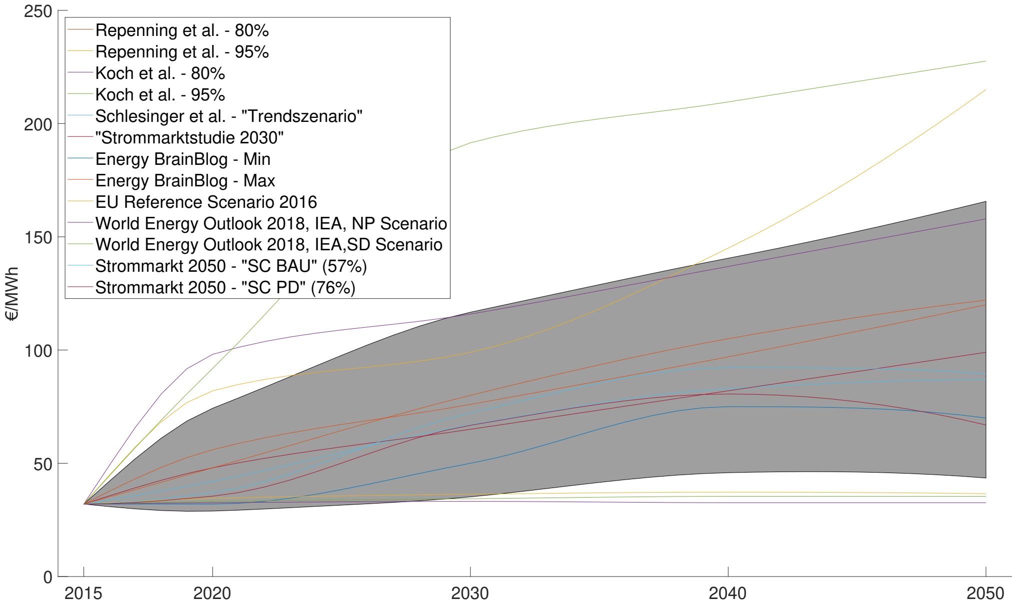


Figure 1: Development curves of the future electricity-only market prices according to existing scenario studies [2, 5–7, 11, 25, 39, 43]. The investigated uncertainty range of the power price development in this study (grey area) is defined by the mean of all curves ± the according empirical standard deviation.

### *2.3. Sensitivity analysis*

In this paper, the variance-based sensitivity analysis of Sobol' was applied to systematically assess which uncertain input factors are responsible for the uncertainty in the model output. When aiming to quantify the relative importance of input parameters $p$=*1..k* for determining the value of an assigned output variable $f(p)$, variance-based methods are proven versatile and effective among the various available techniques for sensitivity analysis of model outputs [42]: "Unlike experimental design, where the effects of factors are estimated over levels, variance-based methods look at the entire factors distribution, using customarily Monte Carlo methods of various sophistication."

Sobol' sensitivity analysis studies the scalar model output $f(p)$ if the model parameters are varied within their uncertainty range. After $N$ model runs with different parameter sets, the variance $V = V(f(p))$ of the scalar output $f(p)$ is split into component variances $V_i$ from individual parameters or parameter interactions. The first order model sensitivity to each parameter $p_i$ is quantified with the first-order Sobol' index $S_i$, also known as the main effect. The total-order Sobol' index $S_{Ti}$ represents the total effect of parameter $p_i$ and its interaction with all other parameters. A more detailed description of the Sobol' method and how to apply it on models can be found in Saltelli [41], Saltelli et al. [42].

In this study, an algorithm was chosen to calculate the Sobol' main effect and total effect with $N(k+2)$ model evaluations [41]. The method used to calculate the Sobol indices requires two independent matrices $A$ and $B$ both containing $N$ sets of $k$ parameters. In this case, $k$ is the number of parameters and $N$ is the sample size used for the random value estimate for parameters being varied. For the random value estimate, Cuntz et al. [19] recommends the use of e.g. stratified sampling such as latin hypercube sampling, which was applied in this study with a sample size of $N = 1000$. The latin hypercube sampling technique evenly samples from the probability distributions [30]. The additionally required matrix $A_B^{(i)}$ has all columns of $A(B)$ except the $i^{th}$ column, which comes from B(A). The exact formulation of the indices $S_i$ and $S_{Ti}$ are chosen from Table 2 (b), (f) of Saltelli et al. [42], which are described as being *best practice*.

$$S_i = \frac{1}{V}\left[\frac{1}{N}\sum_{j=1}^{N} f(B)_j \left(f(A_B^{(i)})_j - f(A)_j\right)\right] \tag{1}$$

$$S_{Ti} = \frac{1}{V}\left[\frac{1}{2N}\sum_{j=1}^{N} \left(f(A_B^{(i)})_j - f(A)_j\right)^2\right] \tag{2}$$

Both Sobol' indices range from 0 to 1. $S_{Ti} \geq S_i \geq 0$. If $S_{Ti} = S_i = 0$ the parameter is non-influential. If $S_{Ti} = S_i$ there is no interaction of the $i^{th}$ parameter with other parameters.

The scalar model output $f(p)$, on which the Sobol' indices are applied to in this study, is defined by calculating the share of the consumed biomass $\dot{m}$ of each biomass product $b$ in relation to the sum of all biomass products used for heating. In each case, the biomass was summed over the complete time span *t=2015-2050.*

$$f(p = 1..k) = \frac{\sum_{t=2015}^{2050} \dot{m}_{t,b}}{\sum_{t=2015}^{2050}\sum_{b=1}^{20} \dot{m}_{t,b}}$$

The optimization model is evaluated $N(k + 2) = 34000$ times. To overcome the computational burden, the calculations were executed on a model server grid with 32 cores having 64 logical processors, using 140GB of RAM in peak and 34 optimizations running in parallel. The total calculation time took $\sim$ 60 hours.

A visual depiction of how the Sobol' method is applied to the ESOM can be found in Fig. 2. Based on the significance of the calculated Sobol' indices, scatter plots and min/ max plots are generated to further analyze how the significantly influencing input parameters impact the model outcome $f(p)$. Based on this analysis, a solution space is quantified for the future cost-optimal use of biomass in the German heat sector under uncertain developments.

## 3. Results

### *3.1. Results from sensitivity analysis*

For 16 out of the 20 defined biomass products the share $f(p)$ was $< 3\%$ in 95% of the 34000 model evaluations. For 12 products, the share was even $< 1\%$ in 99% of all model runs. Consequently, the market shares of 16 biomass products were considered unrelevant and the sensitivity assessment was further investigated on only four of the 20 biomass products, which are:

- Wood chips (from residues)
- Wood pellets (from residues)
- Log wood
- Miscanthus chips

These four biomass products use $> 90\%$ of the available biomass potential in 98.8% of the model runs and $> 95\%$ of the available biomass in 92.7% of the model runs.

The calculated Sobol' indices for the four relevant biomass products are shown in Fig. 3. It is found that 24 of the 32 investigated parameters are non influential to the defined model output and only 8 parameters have an impact on the competitiveness of the biomass market shares. Due to the significant difference in the values of $S_{Ti}$ to $S_i$ of the parameters “power price” and “gas price”, an interaction of these two parameters can be identified. However, from the Sobol' indices and the parameter interactions it cannot be analyzed how the 8 parameters impact the model output f(p). Therefore, scatter plots were generated for each Sobol' index with a value $> 0.05$. Input/output scatter plots are a simple and informative way to provide an

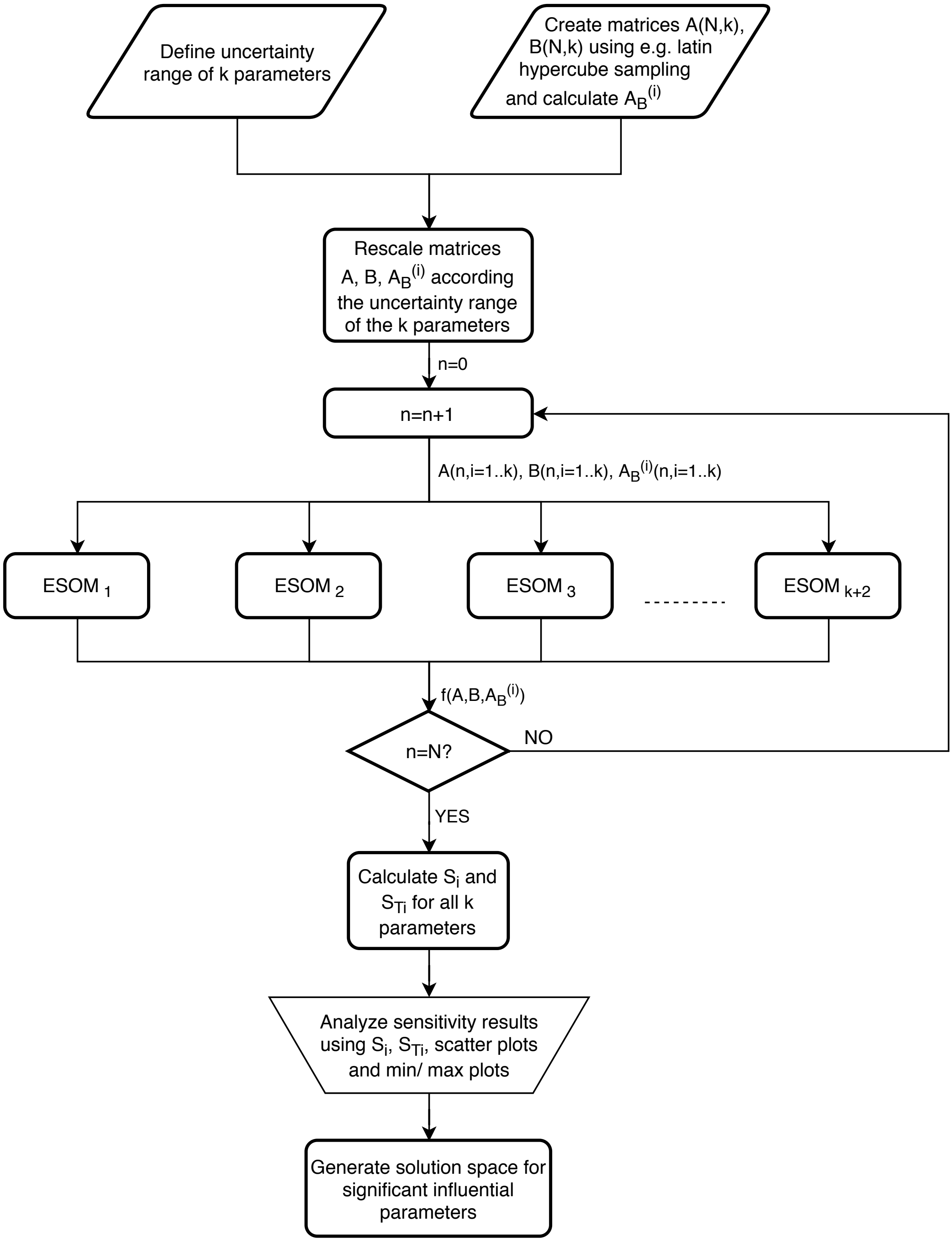


Figure 2: Flow chart illustrating how the Sobol' method is applied to the ESOM and how further analyses are conducted in this study. $\mathrm{ESOM}_{1..k+2}$ have the exact same model formulations, only the input parameters are varied according to the Sobol' method. The flow chart shows one possibility to overcome the computational burden by applying parallel computing.

immediate visual depiction of the relative importance of the parameters [40]. More shape or pattern in a scatter plot indicates that f(p) is more sensitive to the corresponding parameter. A high penetration over a wide range of outcomes is a strong indication of robustness [22, 50].

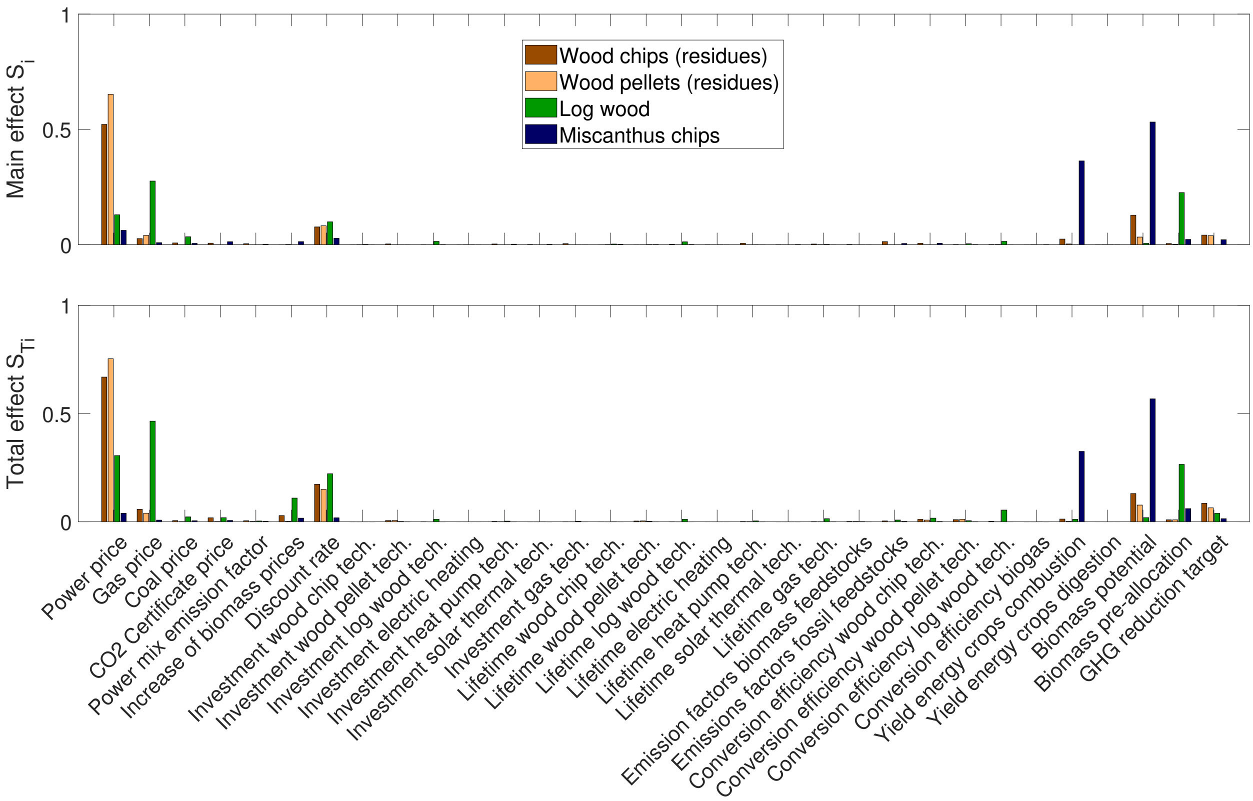


Figure 3: Sobol' indices for the 32 investigated input parameter uncertainties on the four identified, relevant biomass products. Both Sobol' indices range from 0 to 1. $S_{Ti} \geq S_i \geq 0$. If $S_{Ti} = S_i = 0$ the parameter is non-influential. If $S_{Ti} = S_i$ there is no interaction of the $i^{th}$ parameter with other parameters.

In 12 of 18 scatter plots a pattern could be identified, affecting 7 parameters, see Fig. 4 and 5. From the Sobol' indices as well as from the scatter plots, it is found that the uncertainty in the future power price development has the greatest impact on the share of wood chips and wood pellets, which in most cases hold the greatest market shares. High power prices favor wood pellet market shares, while low power prices favor wood chip market shares. In the scatter plot of Fig. 4, it is found that the power price influences the upper and lower bounds of the product shares, indicating that this parameter affects the choice of the biomass product. While e.g. the uncertainty of the parameter "biomass potential" only affects an upper or lower bound, indicating that the parameter does not affect the choice of the product, but does have amplifying effects.

The log wood shares are significantly influenced by four parameters, but only in a minority of the cases. In only 5.7% of all model runs, product shares of log wood rise up to 20 - 45%, mainly influenced by low power prices and high gas prices. This confirms the findings from the Sobol' indices that the parameters "power price" and "gas price" are interacting. High log wood market shares only apply when power prices are low and gas prices are high. A variation of only one of the parameters does not lead to this result. However, the low penetration for high log wood shares over a wide range of outcomes indicates that the use of biomass in great amounts of log wood is not a robust result. Market shares of Miscanthus chips increase with higher yields of energy crops used for combustion and lower amounts of biomass available.

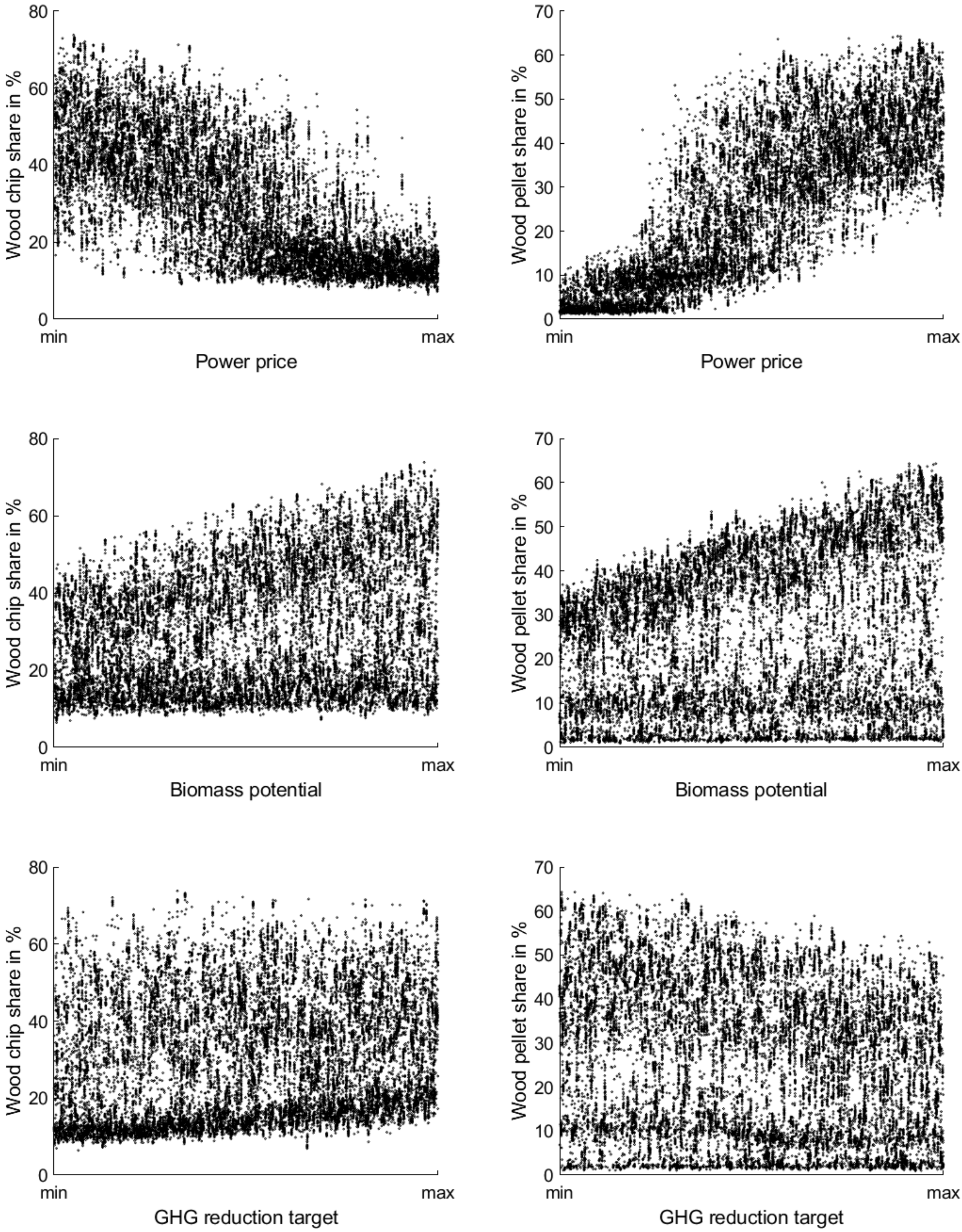


Figure 4: Input/output scatter plots for the wood pellet (residues) and wood chip (residues) market shares, depending on the shown parameters (x-axis label). Each dot represents one of the 34000 model runs. The x-axis represents the uncertainty range of the input parameter according to Table 1.

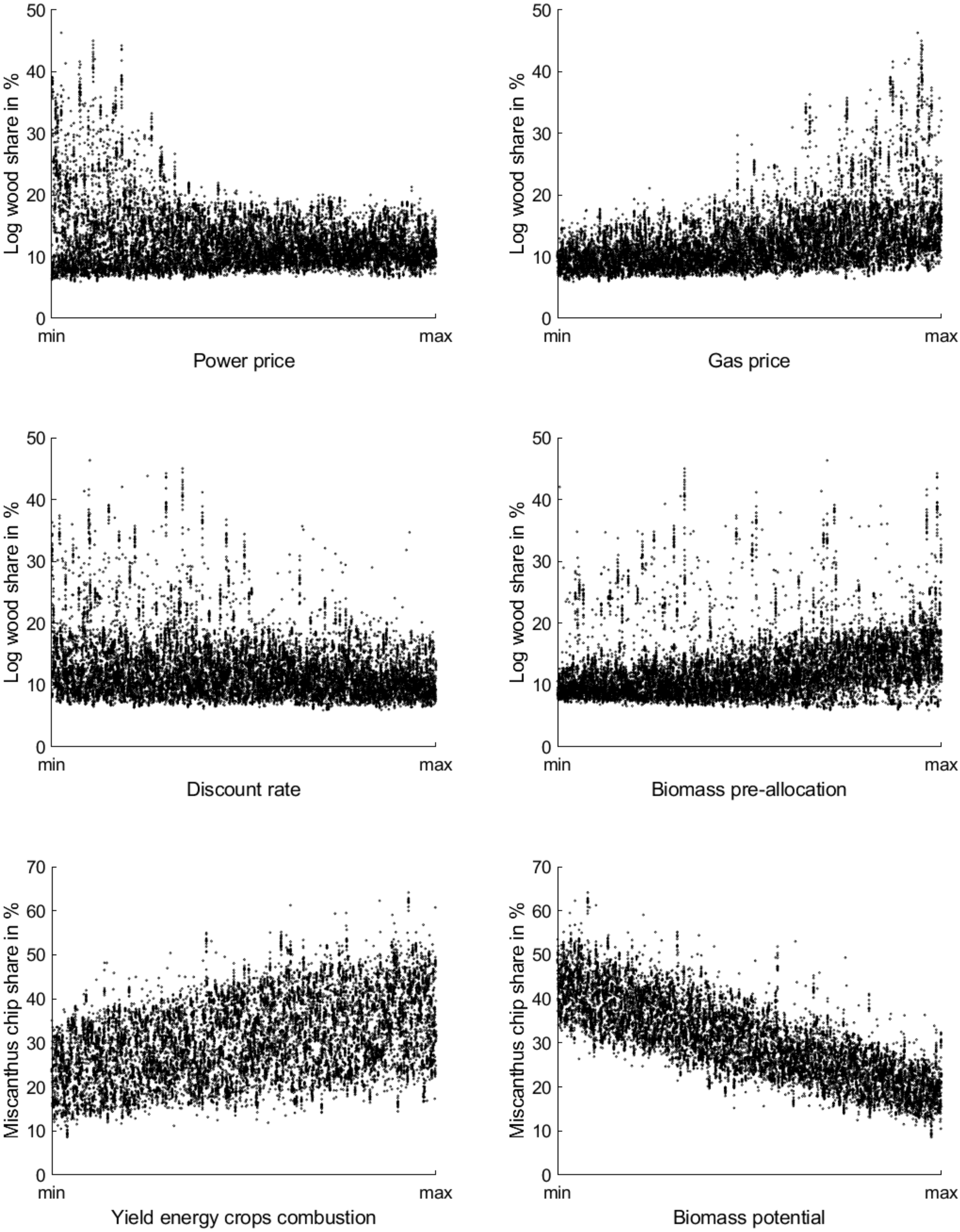


Figure 5: Input/output scatter plots for the log wood and Miscanthus chip market shares, depending on the shown parameters (x-axis label). Each dot represents one of the 34000 model runs. The x-axis represents the uncertainty range of the input parameter according to Table 1.

*3.2. Solution space*

The analysis of the Sobol' indices and the scatter plots identified the uncertainty of six input parameters to be significantly influential on the market shares of four biomass products (the parameters "biomass potential" and "biomass pre-allocation" have been aggregated, as they have the same effect). This section reveals into which heat technology concepts these biomass products are distributed in. Therefore, 32 model results have been calculated with the maximum and minimum value developments of the six identified and significantly influential parameters. Fig. 7 and 8 in the appendix show which wood based technology concepts are competitive in the case of min/ max parameter values. Based on the analysis of these two figures and the scatter plots, the following impacts of the six parameters on the technology market shares are identified:

- **Power and gas price**: major impact on the technology competitiveness
- **Climate target**: changes the technological competitiveness from 2040 onwards; a higher climate target increases the competitiveness of wood chip technologies
- Biomass potential/ biomass pre-allocation: amplifies/ weakens the technology market shares, but does not influence the choice of the technology
- High discount rate: amplifies the market share in favor of wood chip technologies and against log wood gasification systems, but does not change the technology choice
- Yield perennials: negligible influence on the competitiveness of the selected technology concepts

Evaluating sensitivity analysis, input/ output scatter plots and min/ max plots revealed that the choice of the cost optimal bioenergy technology concepts is found to be significantly influenced by only three out of 32 parameters: the power price, the gas price and from 2040 onwards by the climate target. Additionally two parameters have amplifying effects on the market share of the chosen technologies, the available biomass potential and the applied discount rate. Based on these results, a solution space was calculated for the possible bioenergy technology choices, considering the uncertainties of the three significantly influential input parameters.

Fig. 6 shows the calculated solution space for bioenergy technologies in the German heat sector under the min/ max development curves of the future power and gas price. Within the figure, only the relevant bioenergy technology concepts are shown, leaving out fossil references, alternative renewable technologies and uncompetitive bioenergy concepts. For hybrid systems, only the solid biomass net energy shares of the concepts are displayed in order to have a comparable depiction of the biomass utilization. In cases of maximal power prices, the gas price is found not to be influential. Therefore, the climate target was also varied for maximum power prices, showing the impact of that parameter from 2040 onwards. The total net energy market share of all bioenergy technologies is in the range of $10-25\%$ from 2030 onwards. The absolute values can be seen in Fig. 6, 7 and 8 (in comparison: the future net energy demand for heating is 4500 PJ in 2015 decreasing to 2700 or 3100 PJ in 2050).

The calculated solution space in Fig. 6 shows that for low power and low gas prices, the available biomass potential is almost exclusively used in the form of wood chips in high temperature industry applications. With rising gas prices, biomass is utilized in industry applications of different temperature levels. Additionally, major biomass shares are applied in log wood gasification boilers combined with solar thermal systems in the private household sector. When power prices are high, all other parameters play a minor role on the technology choice. Hybrid systems used in the private household sector, which combine solid bioenergy technologies with heat pumps and PV, dominate the market with an additional share of wood chips in high temperature industry applications. The main hybrid system in place is a CHP (torrefied-) wood pellet combustion system. Minor biomass shares are applied to log wood gasification systems or log wood stoves in the private household sector. Towards 2050, a high climate target favors the use of biomass in high temperature industry applications, resulting in a shift of almost the complete available biomass away from hybrid systems into high temperature industry applications. In summary, the cost optimal allocation of the available biomass potential mainly shifts between several sub-sectors of the private household and industry sector, driven by the development of the power-, gas price and GHG reduction target.

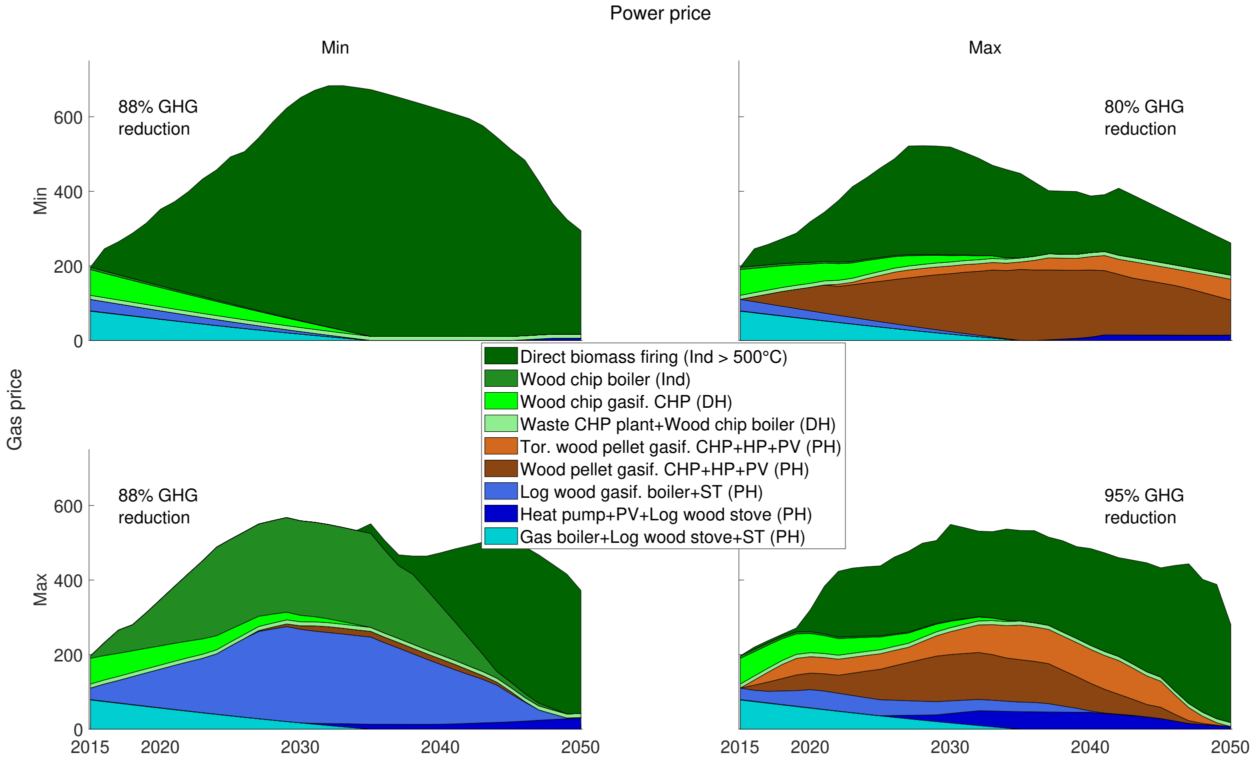


Figure 6: Calculated solution space for the choice of bioenergy technologies, considering the defined uncertainties of the input parameters in Table 1. Displayed are the net energy market shares of the relevant bioenergy technologies in PJ. Within the figure only the relevant bioenergy technology concepts are shown, leaving out fossil references, alternative renewable technologies and unrelevant bioenergy concepts. For hybrid systems, only the solid biomass net energy shares of the concepts are displayed in order to have a depiction of the biomass utilization. All other investigated parameters, beside the "power price", "gas price" and "climate target", are set to a medium value from Table 1. Ind = Industry; DH = District Heating; PH = Private Households; CHP = Combined Heat and Power; HP = Heat Pump; PV = Photovoltaic; ST = Solar Thermal

## 4. Discussion

The investigation performed in this paper intends to improve the robustness of the outputs from optimization modeling and for their use in for providing policy insights. Compared to former scenario analyses [23, 24], the confidence in the robustness of the model results is highly improved. Instead of the investigation of four scenarios, assessing only the min/ max values of two parameters, a wide decision landscape under alternative futures was explored, covering the majority of developments with expected uncertainty, rather than all uncertainties in general. With this method, it is possible to represent the relationship between input factors and model outputs, which improves model transparency and unpacks model structure. The results confirm findings from the scenario analysis, add new findings and increase confidence in the findings.

First of all, it is found that in 99.6% of all 34000 model evaluations, climate targets could be fulfilled. This result shows that it is possible to have a successful heat transition in Germany and confirms the robustness of that statement. Of course, this is not in line with current developments in terms of meeting climate targets in the German heat sector. However, this study intends to show that, from a techno-economic point of view, it is possible to meet the climate targets in the heat sector despite all uncertain future developments. Policies or federal granting is not considered in this analysis. Second, it is found that bioenergy is a competitive option under the investigated uncertainties. In all cases, almost the complete available biomass potential, pre-allocated for heating, is used in the model. This results in total bioenergy net market shares of $10-25\%$ from all heating applications in Germany. Third, robust technology concepts for the future use of biomass under investigated uncertainties are identified, being significantly influenced by only a few parameters.

With the outlined method, the source of uncertainty in technology choice, could be narrowed down from 32 to only three parameters, confirming the findings from Saltelli [40] that only a few factors create almost all uncertainty, while the majority only make negligible contributions. In this study, the choice of the bioenergy technology concepts is highly influenced by the future development of the power and gas price. Additionally, the defined climate target changes the technological competitiveness from 2040 onwards. Moreover, two parameters, the available biomass potential and the discount rate, have amplifying effects, but do not influence the technology choice significantly.

The most robust technology for the future use of biomass is found to be the use of wood chips in (high temperature) industry applications. This conclusion is derived from the scatter plots of Fig. 4 and 5. A combined minimum market penetration of wood chips and Miscanthus chips of $\sim 25\%$ and above over a wide range of outcomes can be identified, which is a strong indication of robustness [22, 50]. Additionally, the identified solution space reveals major wood chip technology market shares of $\sim 30 - 90\%$ in all cases, see Fig. 6. Finally, if a climate target towards 95% GHG reduction is aimed for, the use of wood chips from residues and energy crops in high temperature industry applications is found to be the most cost efficient way to reduce the heat based emissions in all investigated cases, see Fig. 7.

Nevertheless, with rising power prices, hybrid CHP (torrefied-) wood pellet shares increase clearly, using up to 60% of the available biomass potential. Again, the scatter plots in Fig. 4 show a high penetration of major market shares over a wide range of outcomes, which again is a strong indication of robustness. This finding confirms the results from former scenario analyses that the synergies from hybrid heat technology systems and their GHG mitigation potential are underestimated and that such systems can substantially contribute to the success of the energy transition in Germany [23, 24].

A unique finding in this study is the competitiveness of log wood gasification systems, when power prices remain low and gas prices increase clearly. However, from the scatter plot in Fig. 5, a low penetration for high log wood shares can be identified, leading to the conclusion that log wood gasification systems are not a robust technology choice under future uncertainties.

Available land for energy crops is, for all model evaluations, nearly exclusively cultivated with Miscanthus, despite the large range in which the yields of Miscanthus have been varied in the sensitivity assessment ($\pm 33\%$). Again, the scatter plots in Fig. 5 reveal robust market shares for Miscanthus, leading to the conclusion that the use of Miscanthus for reaching the climate targets in the German heat sector needs to be considered, despite several major barriers arising, to a large extent, from the necessary long term commitment [48]. These factors are not represented in the optimization model. A model run excluding perennial crops was performed in a former study [24], which resulted in the cultivation of maize silage for the use of biomethane in high temperature industry applications in the long term. This could be a possible business case for biomethane in the heat sector, although it was not found to be competitive in the uncertainty assessment of this investigation.

Overall, confidence in the robustness of the model results is highly improved. Additional findings could be identified and several findings from former scenario analyses can be confirmed with this study, e.g. bioenergy is not found to be competitive in the district heating and the trade and commerce sector. A robust statement about the feasibility of the German heat transition under future uncertainties is made and wood chip and pellet technologies are found to be competitive bioenergy options to fulfill the climate targets in Germany. The use of biomass in the form of wood chips in (high temperature) industry applications is found to be the most robust choice in all cases, while the hybrid CHP wood pellet systems are only robust, favorable options given increasing power prices. Additionally, when doing scenario analyses, doubts exist regarding the results, arising from the uncertainty of the model input factors. With the method applied in this paper, confidence in the robustness of the results and their use for providing policy insights is deeply improved. To the authors' knowledge, similar research, beyond simple scenario analysis, has not been performed on the future use of biomass in the German heat sector. Especially, the application of the Sobol' method in energy optimization modeling is a novel approach performed in this paper. It can serve as a case study or guideline for other researchers, who want to adapt this method and increase robustness in their ESOM results, which is highly recommended within best practice formulations for ESOMs [20]. The use of the Sobol' method identifies which parameters significantly impact the model outcome. Using scatter plots to explore these findings reveal how these parameters affect the model outcome and can focus scenario analyses.

The quantification of a solution space for competitive technologies is one possibility of how to exploit these findings. A step by step description of the performed method in this paper can be found in the flow chart of Fig. 2. Theoretically, this method can be applied to any ESOM or region, the main drawback of the method is the computational cost to calculate the Sobol' indices. Therefore, the model run time has to be in the range of minutes or less. Based on the individual model run time, the number of parameters to be investigated and the number of sets required for the random value estimates need to be determined. An evaluation of the suitability of this method is recommended in each case.

**Limitations:** Uncertainties have become one of the major challenges of ESOMs. A wide decision landscape under alternative futures was explored in this paper. Of course, not all possible future uncertainties of the input parameters can be considered, but the majority of developments with expected uncertainty were investigated. However, it is assumed that all input parameters are independent of each other, which may not be the case. Future correlations between the parameters can occur. Nevertheless, they are hard to be expressed in numbers today and the sample size needed to compute sensitivity measures for nonindependent parameters is much higher than in the case of uncorrelated samples [40].

Uncertainties referring to the imperfect mathematical relationships within the model, so called structural uncertainties, have not been investigated [33]. For example, spatial aspects of biomass availability, spatial heat demand distributions, an increased temporal resolution nor the individual investment behavior of homeowners were considered. Especially in the heat sector, with millions of homeowners, the individual behavior is potentially influential for the future market development. However, the research question investigated in this paper focuses on cost optimal solutions to fulfill the climate targets in a future German heat sector, for which the individual behavior is not considered to be imperative. However, increasing the annual resolution to an at least monthly one seems worthwhile to investigate, since the heat demand, PV yield, etc. varies seasonally.

Of course, modeling has its limits, as does this optimization model. In a future German energy system, sectors are expected to be strongly connected. Consequently, all energy sectors should ideally be modeled together and the available biomass potential could be optimally allocated over all sectors. Due to the complexity of the complete energy system, this would lead to high model run times, making it difficult to perform a systematic sensitivity analysis as done in this paper. However, with increasing shares of power based heating technologies, the heat sector is expected to be strongly connected to the power sector. Therefore, a new approach was established to link the power and heat sector without modeling the complete power sector, see Jordan et al. [24].

Additionally, the level of detail in a model is limited. The private household sector is depicted in a high level of detail, which was not possible for the industry and district heating sector due to the limited available data bases. Further research in this direction is recommended from the authors' view.

## 5. Conclusions

The application of the Sobol' method in energy optimization modeling is a novel approach, which can serve as a case study or guideline for other researchers. The performed method identifies parameters which impact the model outcome and how they do so. Theoretically, the method can be applied on any ESOM or region, the main drawback is the computational cost, for which the model run time has to be in the range of minutes or less.

In this paper, the applied method identified bioenergy as a robust, cost competitive option to fulfill the climate targets in a future German heat sector under a wide range of uncertain developments. The most robust use of biomass is found to be in the form of wood chips from residues and Miscanthus in (high temperature) industry applications. With rising power prices, the use of biomass in hybrid combined heat and power (torrefied-) wood pellet technologies in the private household sector is an additional robust, competitive option. Both technological concepts have the potential to close gaps in a sustainable energy system and should be considered for the future use of biomass in the German heat sector, when designing policies.

The future competitiveness of the identified, robust technology concepts is mainly influenced by the development of the power price, gas price and the defined GHG reduction target. Consequently, when designing policies, these factors should be the focus. Future shortages in the supply of renewable power need to be represented in high power prices. Additionally, solid biomass is required to be sustainably available for heating purposes and the use of Miscanthus for heating should be discussed and considered, despite the major barriers arising from the necessary long term commitment of growing perennial crops. A defined GHG reduction roadmap needs to be established, committing the industry to decarbonize its processes. When GHG reduction is mandatory for the industry sector, technologies using solid biomass as a feedstock is found to be a robust, competitive option for high temperature industry applications. The outlined recommendations are based on a comprehensive sensitivity analysis, investigating a wide range of uncertainty, and therefore provide policy insights with a high level of confidence.

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## 7. Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.17632/v2c93n28rj.2

## 8. Appendix B.

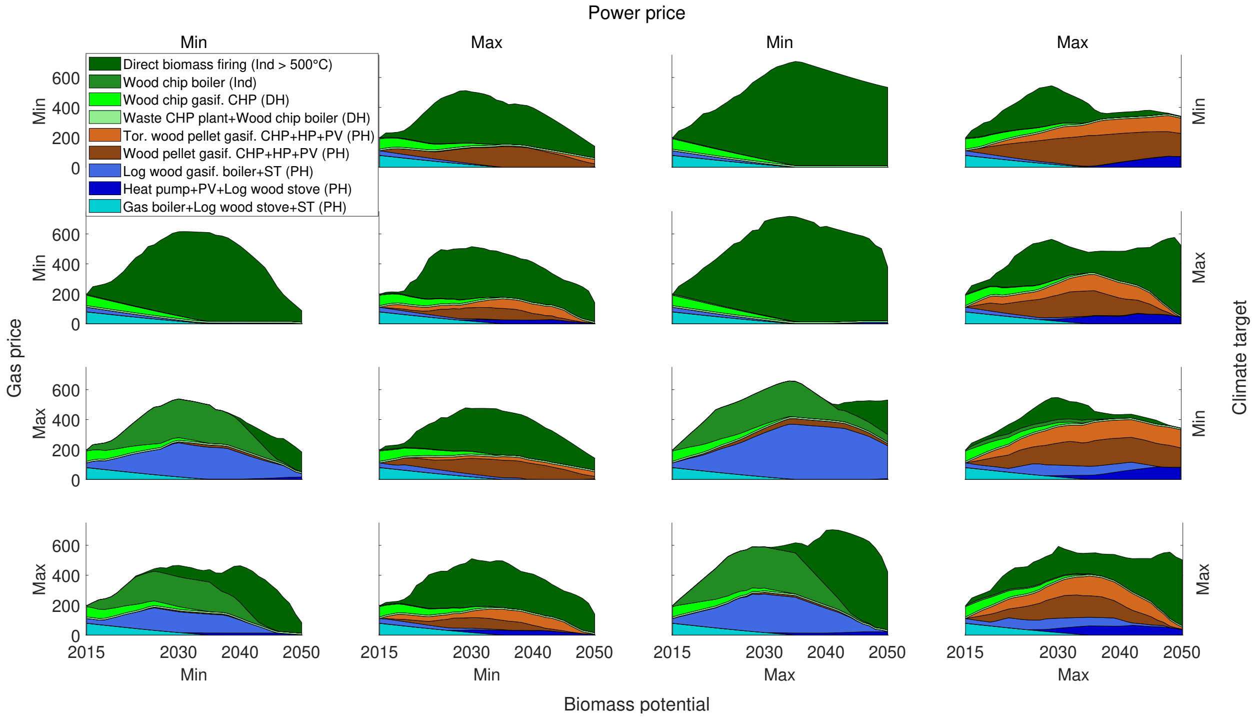


Figure 7: Net energy market shares of the relevant solid bioenergy technologies in PJ for the min/ max developments (see Table: 1) of influential parameters (x-/y-labels). Ind = Industry; DH = District Heating; PH = Private Households; CHP = Combined Heat and Power; HP = Heat Pump; PV = Photovoltaic; ST = Solar Thermal

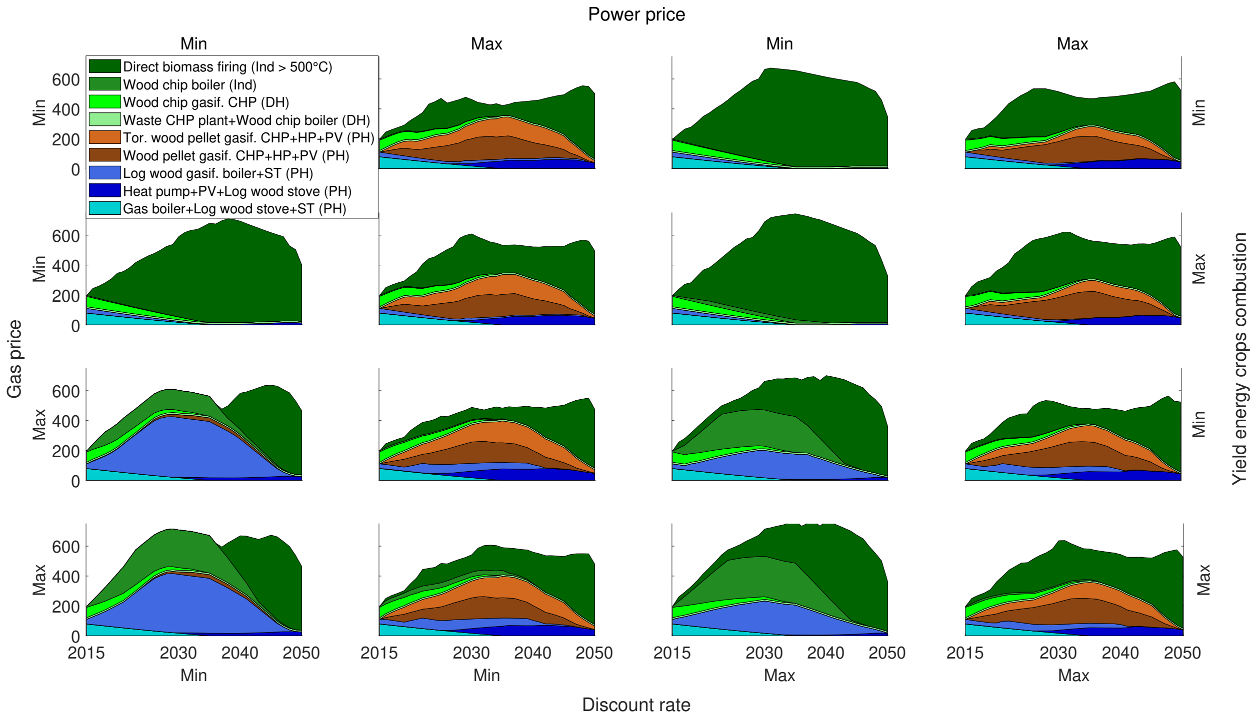


Figure 8: Net energy market shares of the relevant solid bioenergy technologies in PJ for the min/ max developments (see Table: 1) of influential parameters (x-/y-labels). Ind = Industry; DH = District Heating; PH = Private Households; CHP = Combined Heat and Power; HP = Heat Pump; PV = Photovoltaic; ST = Solar Thermal

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