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Fuel choice in industrial steam generation: Empirical evidence reveals technology preferences

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ABSTRACT

Scenario analysis of the energy system relies largely on model calculation and underlying techno-economic data. In the industrial context, the influence of behavioral aspects has been neglected or is subject to expert-judgment. Empirical evidence on technology preferences is scarce. In this publication, we present original survey results for preferences in industrial steam generation technologies in Germany. Additionally, we compare the performance of a set of preference parameters derived from these results with expert-judgment. We find that in the sample, coal- and oil-based generation is perceived as less attractive than biomass- and natural gas-based generation by a value equivalent to 4.40 €ct/kWh and 2.26 €ct/kWh, respectively, for experienced users. This effect is stronger for inexperienced users (+55%). Different results were obtained in an energy system model using these stated preferences and expert judgment (considering revealed preference data). This might hint at a shift of preferences.

1. Introduction

Scenario analysis of long-term energy futures has to address multiple types of uncertainties. Assumptions on future developments are the most prominent: economic or population growth, technological advances, energy prices and many others. The direction these framework values take, determine largely the outcome of the analysis [1]. For energy models dealing with industry, the consideration of preferences in investment decisions is a rather new concept, for which empirical data are scarce. Therefore, not only the future development, but also the current status is uncertain. The approach applied in this publication originates from research of private consumer behavior, e.g. in tourism and transportation [2,3]. Behavioral aspects have not been the focus of industry models, as decisions made by companies are thought to be highly rational and thus less influenced by individual or group-specific preferences. However, cost optimizing often does not adequately represent observed technology choice, because among others, factors like fuel handling, status-quo, emissions, future expectations and lack of information also influence the decision outcome. This shows a parallel to the much more investigated field of energy efficiency and its barriers and enablers [4,5]. Accordingly, energy models consider preference parameters beyond cost-optimization, however, they often lack a sound empirical foundation and are instead based on "expert judgement". Few surveys have been conducted to determine preference parameters empirically (e.g. Ref. [6]). Fuel choice models and their parameters are instead often derived from top-down econometric analyses (e.g. Ref. [7]). Empirical evidence on these parameters is scarce, because samples in the industrial context are usually much smaller and harder to come by than in private households. These difficulties are amplified by the heterogeneity of industrial activity.

In this publication, we present a case study on technology choice of companies in the industry sector on the example of steam generation in Germany. Steam generation accounts for about 40% of industrial process heating demand in Germany (and Europe) [8].

We present original data on preferences for generation technologies. Based on the survey results, we derive preference parameters for technology choice and compare them with parameters based on expert judgement. We investigate which parameter set better explains the observed development in Germany during 2008 and 2016 in the energy-demand model FORECAST [9,10]. The steam generation simulation shares elements with the fuel switch model for industrial furnaces described in more detail in Ref. [11].

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The paper is structured the following way: First, the data generation, analysis and the modeling approach are presented. Second, the construction of the preference parameter sets is explained. Third, the respective model outcomes are compared against the observed development.

2. Method and data

2.1. Survey design and results

To analyze the preferences of decision makers regarding steam generators we conducted a survey, targeted at German companies operating steam generators. The survey took place between 7/2018 and 10/2018. The resulting sample consists of 164 respondents from the branches “food processing” (n = 116, 71%), “chemical and pharmaceutical production” (n = 22, 13%), “paper and card-board production” (n = 18, 11%) and other branches (n = 7, 4%). This sample distribution is mostly similar to the distribution of companies in these branches [12] in Germany (excluding the mineral industry).[1] For 53.0% of the respondents, investment decisions regarding steam generators are part of their professional duties (hereafter labeled ‘experienced users'). 28.0% of the respondents work with steam generators although they are not directly concerned with respective investment decisions. Additional 10.4% do not work with steam generators but have done so in the past. The remaining 8.6% of the respondents have no experience with steam generators but consider it likely that they will gain such experience in the future (the latter three categories are labeled ‘unexperienced users'). Respondents who stated that none of the before mentioned categories apply to them were excluded from the sample.

In the survey each respondent evaluated the attractiveness of nine steam generators. The steam generators were characterized by three attributes, whose values were generated randomly within a given range for each of the nine presented steam generators. First, the costs of steam generation in €ct per kWh (possible values: 4, 6, 8 and 10). Second, their reliability as the share of downtime during operational time (possible values: 1%, 0.5%, 0.1% and 0.01%). Third, the used source of energy, which was linked to the amount of CO_2-emissions of the steam generation by respective explanations in the survey (possible values: coal with 100% CO_2-emissions as a benchmark, oil with 80% CO_2-emissions compared to coal, natural gas with 60% of CO_2-emissions compared to coal, biomass with zero net CO_2-emissions[2]).

As the attractiveness of the steam generators was measured by a six step rating scale[3] we analyzed these data by a hierarchical linear model with fixed and random effects, in which the evaluated steam generators are the micro units (cases) clustered within the respondents as macro units (nine cases per respondent) [cf. [13, 14]]. The resulting model explains 76.7% of the variance in the evaluation of steam generators. We find significant effects for all three attributes that characterized the steam generators (costs, downtime, and energy source). In addition, the effect of costs depends on the experience of the respondents with investment decisions in steam generators while there are no such differences for the effects of the other attributes. In particular, an increase of costs by 1 €ct/kWh decreases the attractiveness of a steam generator by 0.263 points at the rating scale for unexperienced users while we find a decrease of 0.410 points for experienced users. For each percentage point of downtime the attractiveness of the steam generator decreases by 0.383 points. Furthermore, a steam generator powered by oil is 0.926 points less attractive than a steam generator powered by biomass. If a steam generator uses coal as energy source instead of biomass, the evaluation decreases by 1.802 points. In contrast, steam generators powered by natural gas are not evaluated significantly different from those powered by biomass. To put the energy-carrier related influence into perspective: a steam generator with average costs (7 €ct/kWh) and average downtime (0.4% of total operational time) powered by biomass is evaluated with a rating of 4.1 (rather attractive).

The interclass-correlation is 0.066. This indicates that only 6.6% of the variance in the evaluation of steam generators is caused by individual differences (e.g. branch or other characteristics at the respondent level) between the respondents. As described above, such differences exist regarding the relevance of costs depending on practical experience with investment decisions in steam generators. However, due to the small interclass-correlation and the limited sample size we do not analyze the causes of such differences.

2.2. Energy system model description

In order to test the survey results in an energy model, we use the model FORECAST. FORECAST is a bottom-up energy system model covering the demand sectors. Among others, it models the choice of industrial steam generation technologies as a discrete choice among competing alternatives. The main determinant of attractiveness in this competition is the perceived utility of the alternatives for the decision maker. This utility is influenced by characteristics of the technology (e.g. investment, fuel costs, available dimension, co-generation capabilities …), framework condition (e.g. taxation, feed-in tariffs) and the decision makers heat demand and preferences. The preferences serve as modifier to the total generation costs and influence the perceived utility of the technology. For example, a coal-based steam boiler may be more attractive where coal is already used in a different context. This may be attributed to existing infrastructure, personnel or general experience. At the same time, fuel prices may be different for some market participants than observable on the macro-level (e.g. biomass in paper industry, natural gas and fuel oil in refineries).

The preferences are coded in parameters (Annex 5). They depict the perceived utility U_k in relation to the plain generation costs based on macro- and techno-economic data according to equation (1). It contains ε_j as market homogeneity, $c_{i=k}$ as costs of an individual technology and $\overline{c_i}$ as average costs of all technologies available to the decision maker.

$$U_k = \varepsilon_j * \frac{c_{i=k}}{\overline{c_i}} \tag{1}$$

The decision for a specific technology is made according to equation (2); with the choice probability π for an individual technology k from all available technologies i as function of perceived utility U. This approach is similar to and partly based on [6,15].

$$\pi_k = \frac{\exp(U_{i=k})}{\sum_i \exp(U_i)} \tag{2}$$

The choice probability is a value between 0 and 1 for each technology and sums to 1. The market homogeneity governs the impact of price differences. High homogeneity increases the impact, as market participants tend to favor the highest-utility option more. However, except for extreme values, all available options will be present in the market, which allows representing niche-applications. For this particular application, a medium-to-high value (7) of the market homogeneity has been chosen, which proved to work with the expert-based

[1] NACE Rev. 2 classification were used to differentiate the branches: food (10, 11, 12), chemical (20), paper (17). From this selection, food makes up for 70.2% of the companies, chemicals for 19.3% and paper for 10.5%. The chemical industry is thus slightly underrepresented in the sample.

[2] This simplification has been made for the survey, neglecting supply chain emissions. The authors are aware that biomass may have relevant carbon footprints when effort e.g. for transport or processing is considered.

[3] The nine steam generators were presented on three pages of the online survey, and therefore coined as options (A, B, C) on each page. Accordingly, each site contained three statements ‘option [A/B/C] is very attractive’. Those could be answered by: *1 = fully disagree, 2 = mostly disagree, 3 = rather disagree, 4 = rather agree, 5 = mostly agree, 6 = fully agree*. Please refer to Annex 1 for this section of the survey (translated from German) and the complete questionnaire in Annex 2 (in German).

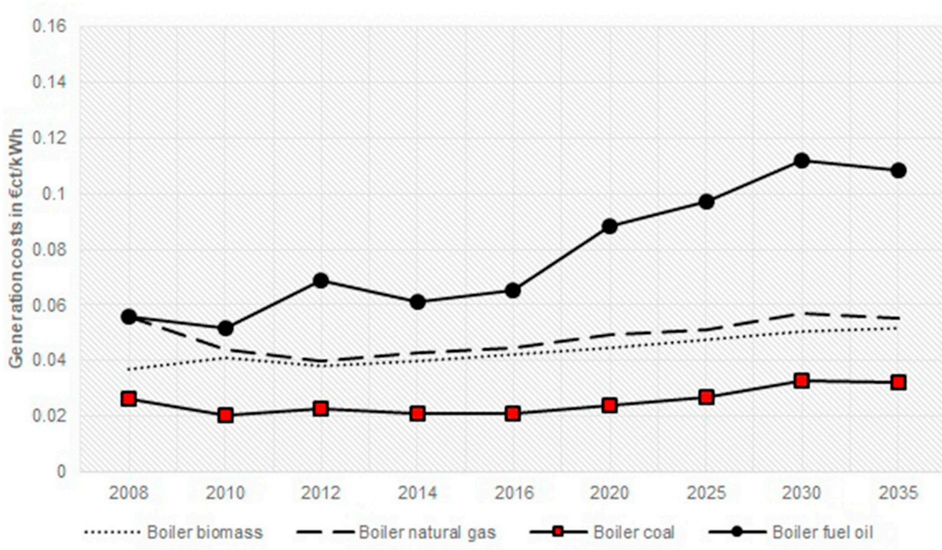

Fig. 1. Heat generation costs of selected technologies (Germany)[6].

parameter set.[4] To illustrate its effect: this value results in a doubled chance to select a given technology over a technology with 10% increased costs. Note that the choice probability relation follows an s-curve, i.e. is most sensitive in the middle range. Thus, decreasing the costs of a very cheap technology does not greatly improve its market diffusion, while cost variations of close competitors can influence it strongly. See Ref. [16] for further model description.

2.3. Energy system model implementation

For the construction of a preference parameter set, the survey results must be interpreted accordingly. The central finding of the survey is, that coal- and oil-based steam systems are evaluated significantly worse than natural gas- and biomass-based systems. For experienced users, this is worth a flat margin of approximately 4.40 €ct/kWh (oil: 2.26 €ct/kWh). This value is calculated by dividing the change of attractiveness due to energy carrier (coal: 1.802 points, oil: 0.962 points, compared to biomass/natural gas as baseline) by the change of attractiveness due to a price increase of 1 €ct/kWh. For experienced users, this price increase is 0.410 points. For inexperienced users, it is weaker (0.263). This means that experienced users value the attractiveness due to price increases higher and, in turn, those due to energy carriers lower. Hence, the effect of energy carrier on technology choice (in monetary terms) is weaker for experienced users.

For the energy system model analysis, we apply only the weaker energy carrier related effect of the experienced users. For the discrete choice-based model, this means that the perceived utility for both technology options is equal, when biomass shows generation costs 4.40 €ct/kWh higher than coal. Due to survey limitations, some assumptions must be made for the model implementation:

- The energy carrier preferences have been collected for ‘steam generation systems' and are applied for both CHP and boiler systems equally, each based on their energy carrier.
- Minor energy carriers with similar emission factors as the ones included in the questionnaire (e.g. biofuel compared to biomass; waste compared to coal) are assumed to have a similar attractiveness.[5]
- The preference-based price increase of 4.40 €ct/kWh (coal) and 2.26 €ct/kWh (oil) is applied as a factor, rather than a flat value. For example, coal-based steam boilers show an average generation price slightly above 2 €ct/kWh between 2008 and 2016 (Fig. 1). Considering the preferences, the price should increase by 4.40 €ct/kWh (to 6.40 €ct/kWh). Hence a factor of 3.2 (rounded) is applied. For oil (average price between 2008 and 2016: 6 €ct/kWh), this calculation yields a factor of 1.4 (rounded). The respective generation costs (c_i in equation (1)) are multiplied by these factors in each year of the model calculations. The relative price differences are maintained throughout the simulation.

Annex 5 shows the resulting preference parameter sets (expert judgment and survey data). The presented factors are applied to the generation costs (e.g. a factor of two doubles the generation costs) which are used to determine the utility (and hence choice probability) of the given technology. In the survey-based set, natural gas and biomass are assigned the factor 1; coal is assigned the factor 3.2, oil 1.4. The expert-based parameter set has been developed over the last years specifically for the model. Its main considerations include operation, required infrastructure, available dimensions and macro-trends (e.g. observed declining fuel oil use in all industrial subsectors and increasing coal use in many industrial subsectors).

3. Results and discussion

The scenario underlying the following calculations is based on [17]. It develops a ‘reference'-scenario with limited transformation, in which fossil fuels are still relevant in 2035. However, focus of this investigation are the relative differences between the parameter sets. Fig. 2 shows the resulting energy demand in both variations for the most relevant energy carriers (80% of total), for the start year 2008, the end of the empiric data [18] 2016 and the end year 2035. The energy carriers

[4] While the concept of market homogeneity can be qualitatively described (e.g. by the number and size of companies active in the market), the quantification for the model is an assumption and should be treated with caution. Qualitatively, this values favours the most economic option but still allows for niche applications. This is similar to the approach [6] pursued with a comparable model.

[5] The model requires input for all considered energy carriers (27), but not all of them could be included in the survey. The energy carriers represented by this analogy are of limited importance for the overall picture (in total 25% of the investigated energy demand, with the biggest shares for district heat (10%) and non-renewable waste (5%). The assumption is made for modelling purposes only.

[6] The heat generation costs have been generated with the energy system model FORECAST. In this publication, they should be treated as assumption.

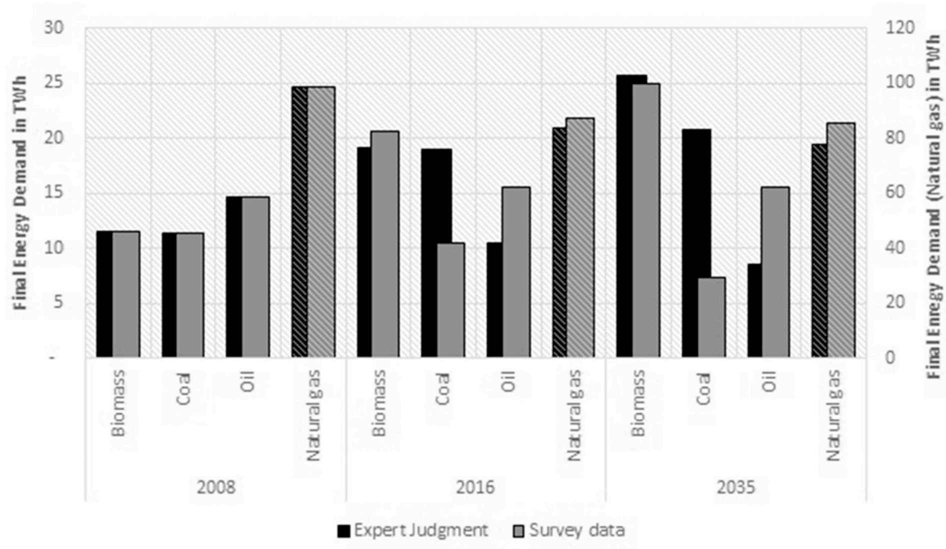

Fig. 2. Final energy demand of selected energy carriers for the parameter set variation (Germany), Natural gas on secondary axis.

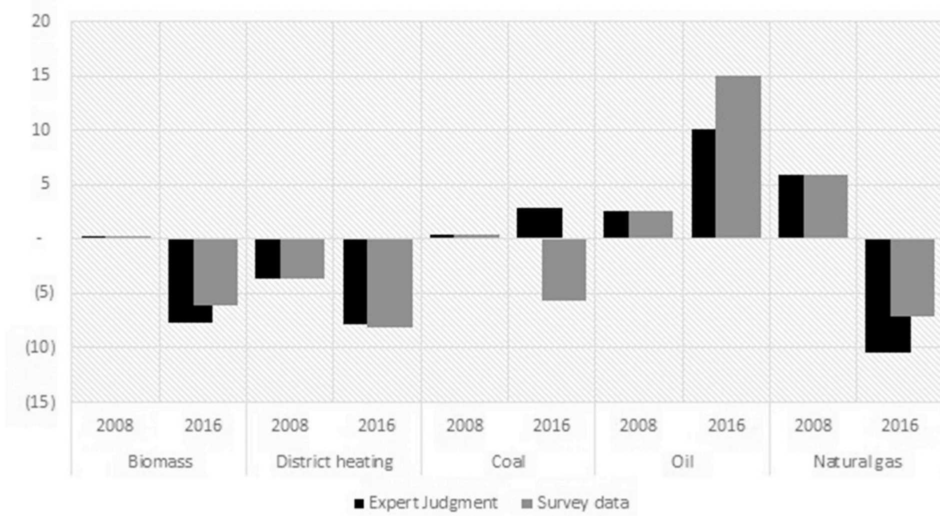

Fig. 3. Difference of final energy demand (model results - energy balance).

biomass, district heating, electricity and natural gas behave similar in both parameter sets. Coal and fuel oil however, show diverting developments. These results are in line with the expectations due to the parameters changes (increased price for coal, reduced price for oil in the survey-based parameter set).

Fig. 3 compares the change in energy demand with the historical development, reflecting the difference between model results and energy balance. A positive value indicates a higher use of this energy carrier in the model than in the energy balance (hence an overestimation of its attractiveness) and vice versa. The survey-based parameter set increases this difference for coal and oil and reduces it for biomass and natural gas. This means that the survey-based parameter set underestimates the use of coal in steam generation, at least in the observed period of 2008–2016. Regarding energy system models-educated design of climate policies, this could create a situation in which the demand for action is underestimated. On the other hand, overestimated coal use (present, though not as strong, in the expert judgment parameter set) can induce inefficiencies. However, the survey data describes the preferences of the sample during the survey (July to October 2018) and the expert judgment data includes information from a longer period, including for example the observation that coal use in industry increased during the last decade in Germany. Therefore, the different preferences do not necessarily contradict each other but might indicate a shift of preferences.

The sample size did not allow for the identification of subsector-dependencies (e.g. higher preference for biomass in the paper industry). The questions were designed to focus the respondents towards their professional opinion and create a situation close to actual investment decisions. To account for a possible bias of the artificial decision-situation we compared our survey-derived parameters with expert-based parameters (which are partly based on observed preferences). However, further research is needed to support either of the approaches.

Despite these difficulties, the presented results are an improvement of the scarce data availability in this field. Further effort should focus on reproducing these results and add the opportunity to investigate sectoral heterogeneity by larger samples.

4. Conclusions

Two conclusions can be drawn from this case study: First, preferences regarding the energy carrier choice in steam generation do exist (coal < oil < biomass = natural gas). The study succeeded in finding empirical evidence, which is so far very scarce. We find that in the sample, coal- and oil-based generation is perceived as less attractive than biomass- and natural gas-based generation by a value equivalent to 4.40 €ct/kWh and 2.26 €ct/kWh, respectively, for experienced users. This effect is stronger for inexperienced users (+55%). However, no such preference can be observed regarding the associated emissions, as such a relation should create a difference between biomass and natural gas. This is especially interesting since the survey instructions explicitly referenced the relative emission factors of the energy carriers.

Second, the preferences identified are strong enough to influence the results of energy system models not only quantitatively, but also on a qualitative level, as they can turn the trend of energy carrier use around. A comparison with expert-judgment, partly based on observed behavior, showed relevant differences. This might indicate that preferences are shifting compared to previous decades.

The results obtained from the different preference parameter sets justify differing policy recommendations even for the same scenario definition. Further research should try to combine the strengths of the approaches. Investigating the reason for the deviation between stated and revealed preferences could yield valuable insights into the decision making process.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.esr.2019.100407.

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