

# Inter-fuel substitution in European industry: A random utility approach on industrial heat demand

Matthias Rehfeldt <sup>a,\*</sup>, Tobias Fleiter <sup>a</sup>, Ernst Worrell <sup>b</sup>

<sup>a</sup> Fraunhofer Institute for Systems and Innovation Research ISI, Breslauer Straße 48, 76139 Karlsruhe, Germany

<sup>b</sup> Utrecht University, Copernicus Institute of Sustainable Development, The Netherlands

## ARTICLE INFO

### Article history:

Received 15 September 2017

Received in revised form

21 February 2018

Accepted 19 March 2018

Available online 20 March 2018

### Keywords:

Inter-fuel substitution

Fuel switch

High temperature

Energy-intensive industry

Energy demand model

Discrete choice

## ABSTRACT

As the majority of industrial emissions stems from heat generation, the choice of fuel is, next to energy efficiency, one of the tools to influence climate impact (and security of supply) in industrial energy use. At the same time, the choice of fuel is not only a matter of price but of the furnace, it is used in. Top-down models often struggle to include technological explicitness, which is especially important to represent the heterogeneous structure of industrial energy demand. In this paper, an approach to apply a discrete choice model to industrial high temperature energy demand is presented. The model's parameters are estimated based on observed fuel choices. The model exhibits an average coefficient of determination of 0.45 when compared to a constant fuel use from 2002 to 2013 in major countries of the European Union. Results suggest that energy carriers are perceived very differently by industrial consumers.

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## 1. Introduction

Heating and cooling accounts for half of the European Union member states (EU28) energy demand. Of this, industrial high temperature process heat (defined here as above 500 °C), makes up for about 1100 TWh (47%) (Rehfeldt et al., 2017 and with a comparable approach Naegler et al., 2015). A vast majority of this energy is supplied by fossil fuels. An important dimension of energy use is the choice of energy carrier, often closely related to the technology choice. Although the purpose of supplying energy, or more specifically heat, to an industrial process is the common ground for all utilized energy carriers, it is evident that not all of them are perfect substitutes. Especially in the context of emission reduction, the choice of fuel use plays a major role (IPCC, 2014). Inter-fuel substitution describes how and to what degree energy carriers can be substituted with each other. It is discussed with regard to climate change (IPCC, 2014, also Newell and Raimi, 2014 in the context of the U.S. shale gas development), health issues (IEA, 2016), security of supply (European Commission, 2014a; b) and cost effectiveness (Gessa-Perrera et al., 2017).

While energy efficiency and its diffusion in the industry as a whole as well as in individual processes is well researched, characterization of processes is often focused on specific energy demand and their energy efficiency. Examples include Worrell et al. (2000, 2010) in the context of the chemical industry and the iron and steel industry or the best available techniques reference documents (BREF, 2001–2018) that describe best the available technologies for several industrial applications and sectors. However, developments in some processes show that incremental efficiency improvements reach technical or physical limits, for example the use of reducing agents in blast furnaces (Fleiter et al., 2013). The choice of energy carriers is seldom addressed.

The use of energy models in all forms has become an important tool in both research and policy advice, especially for the analysis of increasingly complex energy systems. While analyses of energy efficiency focus on technology-rich bottom-up models, econometric models are often used to investigate the fuel mix (see for example Stern, 2010 for a meta-analysis of approaches). These top-down approaches rarely account for technological properties of industrial processes. Therefore, technological restrictions are often neglected in favor of macro-economic effects and analysis. Neglecting technological limitations can lead to overestimated potentials for the use of biomass, waste, recovered heat and inter-fuel substitution in general. Jones (1995) investigated the impact

\* Corresponding author.

E-mail addresses: [Matthias.Rehfeldt@isi.fraunhofer.de](mailto:Matthias.Rehfeldt@isi.fraunhofer.de) (M. Rehfeldt), [Tobias.Fleiter@isi.fraunhofer.de](mailto:Tobias.Fleiter@isi.fraunhofer.de) (T. Fleiter), [E.Worrell@uu.nl](mailto:E.Worrell@uu.nl) (E. Worrell).

of non-substitutable fuels in his econometric analysis of the U.S. industrial energy demand between 1960 and 1992 by excluding non-energy use (coking coal, feedstock and lubricants). He showed that the estimated price elasticities changed significantly compared to an approach without these technological considerations.

The purpose of this study is therefore to develop an approach to include technological detail into fuel switch considerations of energy demand models. To that end, it answers two main questions. Firstly, a decision model for the fuel choice in industrial processes is proposed, to define how market-driven inter-fuel substitution can be explained. Secondly, the decision model is included in an energy demand model, to answer the question, how top-down and bottom-up approaches can be combined. The question is approached by combining technological data of individual processes (e.g. specific energy consumption, temperature level of energy demand) and top-down statistics on subsectoral level (energy balances). The decision model is based on the idea of random utility maximization (RUM). The main hypothesis of this approach is that decision makers maximize their perceived utility, described via directly observable properties (e.g. the fuel price) and not directly observable consumer preferences. The preferences of decision makers may be defined by technological, economical or personal circumstances. They generate heterogeneous decision outcomes among countries and subsectors.

This publication therefore contributes to the topic of inter-fuel substitution by considering technological detail of industrial processes already in the model construction. The bottom-up character of the model system yields higher detail than the usual (econometric) analyses. This can increase the insights gained from energy system models and the policy recommendations derived from them.

The paper is structured as follows. In Section 2, the applied simulation model is described and the main input data sets (observed energy carrier use and price from 1992 to 2013) are presented. The model is applied to historic energy market shares in the EU28. This yields parameters that represent heterogeneity and

behavioral differences among the investigated groups (countries and subsectors), which are presented in Section 3. The paper concludes in Section 4 with a discussion of the methodology and the generated preferences as well as alternative approaches that may complement them.

This publication is accompanied by supplementary data that include the full parameter estimations for selected individual countries and country groups, subsectors and energy carriers.

## 2. Data and methods

### 2.1. Model description

The model is based on a logit-approach of a random utility methodology, as theoretically described by Train (2002) and McFadden (1974, 2000) and applied to the household, transportation and industrial sectors in the bottom-up/top-down hybrid model CIMS (Rivers et al., 2003) and in an industrial context for the IEA's World Energy Outlook (Kesicki and Yanagisawa, 2014). Some key elements for the industrial context (heterogeneity and behavior) are presented in detail by McCollum et al. (2016) in respect to mobility.

The following factors are represented explicitly in the model. Other influences are either considered implicitly or neglected. They are discussed at the end of this article:

- Energy carrier price
- Priced CO<sub>2</sub>-emissions (as tax or trading scheme)
- Market homogeneity of the sectors
- Existing infrastructure and technical properties of industrial processes, expressed as preferences

Fig. 1 shows a visualization of the fuel switch model. The market share consists of price considerations and implicit technological and behavioral influences on the subsector level (e.g. iron and steel industries, non-metallic minerals industries), represented by the

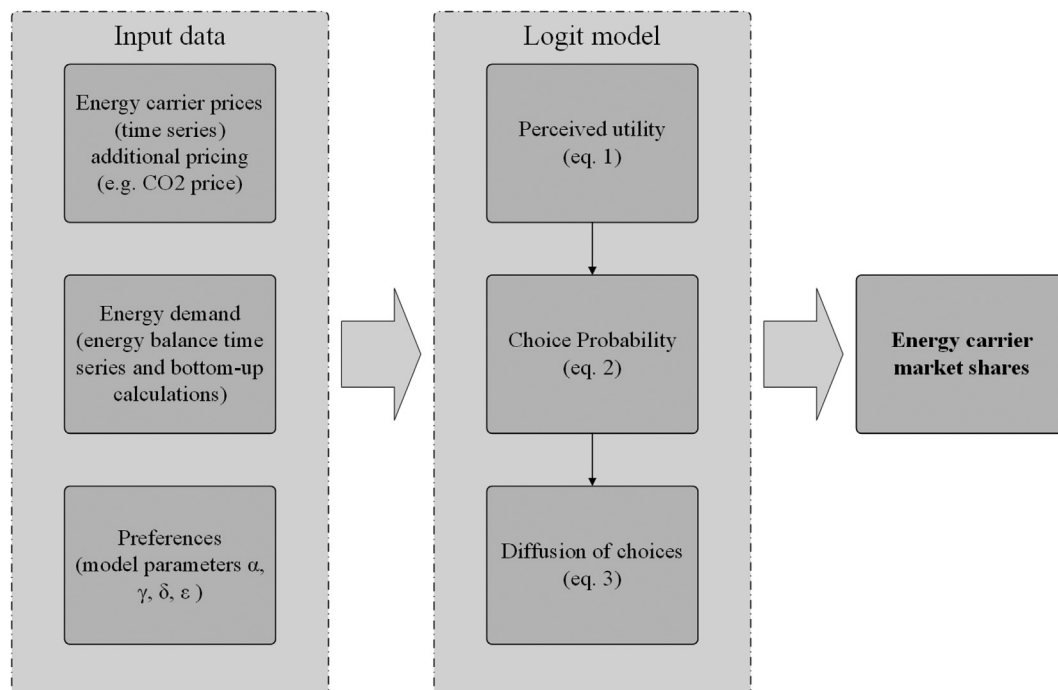


Fig. 1. Representative structure of the fuel switch model.

model parameters. To include explicit technological data, the process level (e.g. blast furnace operations in iron and steel industries) is considered in the model. It introduces an evaluation of individual fuel properties like heating value as well as non-substitutable fuels in processes. This imposes technological limits to fuel switch and enhances the top-down approach. However, this paper focuses on the model description and the definition of the model parameters, as presented in Fig. 1.

The dimensionless perceived utility  $U$  of energy carrier  $i$  in sector  $j$  for any given year and country is defined according to Eq. (1) (modified from Kesicki and Yanagisawa, 2014).

$$U_{ij} = \varepsilon_j * \left[ \alpha_{ij} * \frac{(p_i - \bar{p})}{\bar{p}} + \gamma_{ij} \right] \quad (1)$$

With:

$\varepsilon_j$  as market homogeneity in sector  $j$   
 $\alpha_{ij}$  as price sensitivity towards energy carrier  $i$  in sector  $j$   
 $p_i$  as price of energy carrier  $i$   
 $\bar{p}$  as simple average (unweighted) price of all energy carriers  
 $\gamma_{ij}$  as intangible cost/benefit of energy carrier  $i$  in sector  $j$

Note that compared to the work of Kesicki and Yanagisawa (2014), the time-dependent term in the utility calculation has been removed.

The assumed main driver of fuel switch is the relative price difference (Azar, 2011); that is the ratio of the price difference of an energy carrier and the simple (unweighted) average of all available

energy carriers' prices  $\frac{(p_i - \bar{p})}{\bar{p}}$ . An energy carrier that is more

expensive than the average of all energy carriers will thus yield a lower utility and seem less attractive. This relates to the economic theory of substitute goods, immediately retaining the notion that "the consumer is not seeking gas or oil as such but energy", as Asche et al. (2012) put it. However, in industrial applications, this assumption must be modified to consider process specific requirements. It may very well be that the industrial consumer does seek gas as such because of strong technical preferences. This is modeled by modifying the relative price difference with an energy carrier and sector specific coefficient  $\alpha$  which describes price-related preferences. Hence, shifts of price differences may be seen as less relevant for some energy carriers than for others when evaluating their utility. For example, natural gas is in general more expensive than coal (per unit of energy) but still used extensively.

The parameter  $\gamma$  reflects a structural element of energy carrier choice, which is unrelated to pricing. This may be the existing infrastructure both on-site (distribution and conversion systems) and around it (transport options like pipelines, rivers, rails) as well as other factors (expertise in specific technologies, organizational bias, long-term supply contracts, technical requirements of processes, regulations due to plant location).

$\varepsilon$  is the market homogeneity<sup>1</sup> and describes how transparent the entire relevant market in a sector is (Rivers et al., 2003). For very homogeneous markets, one can assume that individual

market participants have good knowledge about available technologies, energy carriers, manufacturers and suppliers; they consequentially are more likely to choose the alternative with the highest utility. High homogeneity values thus create markets that are dominated by few or even a single energy carrier, while low values blur the perceived differences. In model terms, the parameter depicts how much impact observed data and preferences have on the actual perceived utility.

Additional information, discussion and interpretation of the parameters can be found in 4.3.

The logit-approach (Eq. (2)) yields the choice probability  $\pi$  for an individual energy carrier  $k$  from all available energy carriers  $i$ , in sector  $j$  as a function of the perceived utility  $U$ . The choice probability can be described as a sigmoid curve over the utility. A higher utility yields a higher choice probability (but with diminishing returns for very high values). Note that this does not immediately equal the market share.

$$\pi_{kj} = \frac{\exp(U_{i=k,j})}{\sum_i \exp(U_{i,j})} \quad (2)$$

The choice probability according to Eq. (2) is fed to a diffusion function given in Eq. (3), modified based on Kesicki and Yanagisawa (2014). The difference between the choice probability and the actual market share is defined as potential. Thus, the realization of the choice probability potential for fuel switch slows down as the potential difference decreases. Diffusion in this context is defined as conformity of the actual market share (Share) and calculated choice probability ( $\pi$ ). Due to delaying factors, mainly stock turn-over periods, changed choice probabilities do not instantaneously convert to the market share of energy carriers. Instead, only a certain proportion of the difference between last year's market share and the current choice probability translates into a new market share in any given year (given by the diffusion speed parameter  $\delta$ ).

$$\text{Share}(i, j, t) = \text{Share}(i, j, t-1) + \delta * (\pi(i, j, t) - \text{Share}(i, j, t-1)) \quad (3)$$

With:

$\text{Share}(i, j, t)$  as market share of energy carrier  $i$  in sector  $j$  in year  $t$   
 $\text{Share}(i, j, t-1)$  as market share of energy carrier  $i$  in sector  $j$  in year  $(t-1)$   
 $\pi(i, j, t)$  as choice probability of energy carrier  $i$  in sector  $j$  in year  $t$   
 $\delta$  as diffusion speed parameter ( $0 \ll \delta 1$ )

## 2.2. Input data

The model combines two data sets of the time series to determine the parameter price sensitivity  $\alpha$ , structural factor  $\gamma$ , diffusion factor  $\delta$  and market homogeneity  $\varepsilon$ :

Energy carrier price from 1992 to 2013 (OECD/IEA, 2000–2016)  
 Energy carrier market shares (Eurostat, 2017)

Energy carrier price time series published by OECD/IEA (2000–2016) for the energy carriers light fuel oil, heavy fuel oil, natural gas and steam coal in industry on the country level, including taxes, are used for model calibration. The resulting energy carrier prices are shown in Fig. 2 (example for Germany). Other energy carriers, that are not included in these time series, had

<sup>1</sup> The terms "homogeneity" and "heterogeneity" here are used to describe different concepts: While "market homogeneity" speaks of a property of the observed group (measuring the aggregated degree of information about the group a member of it can have), "heterogeneity" speaks of a model property (the ability to differentiate among groups). They are therefore of different quality and should not be confused.

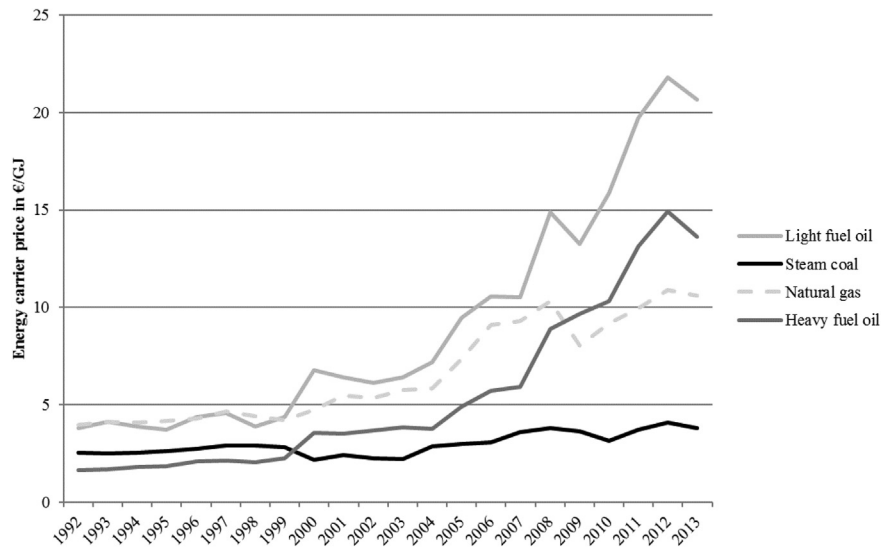


Fig. 2. Energy carrier prices (own illustration, data source: OECD/IEA, 2000–2016) used for model calibration, example for Germany.

to be estimated based on these figures. Table 1 shows relations and the coupling of other energy carriers used where prices are not included in OECD/IEA (2000–2016). As an example, time series on solid biomass prices are not available. The assumed price development for biomass is estimated to be related to the price path of coal, increased by the factor 2. Thus, the price for solid biomass will always be two times higher than the price for coal (before taxes or CO<sub>2</sub> pricing) in a given country. Stack gas, on the other hand, is coupled to the price development of natural gas with a factor of 0.1 due to its low heating value.

### 2.3. Model fit

Based on the data presented in the previous sections, the discrete choice parameters  $\alpha$ ,  $\beta$ ,  $\gamma$  and  $\delta$  are found via a regression using ordinary least squares. These parameters implicitly reflect preferences in sectors and countries regarding the choice of energy carriers. As such, they are regarded as stable over time. The following restrictions are applied to the model regression (also see discussion):

- $-10 < \alpha < -1$  (fuels)
- $-10 < \alpha < -0.1$  (electricity)
- $0 < \gamma < 10$
- $0.1 < \delta < 1$
- $0.1 < \epsilon < 5$

The model fit inverts the model workflow as presented in Fig. 1, as it finds model parameters that fit an observed market share development (Fig. 3).

Table 1  
Price path estimates for other energy carriers.

Coupled energy carrier	Base energy carrier (OECD/IEA 2000–2016)	Factor
Derived gases	Natural gas	1
Waste	Natural gas	0.1
Stack gas	Natural gas	0.1
Biofuels liquid	Light fuel oil	1
Coke	Coking coal	1
Biomass solid	Steam coal	2
Lignite	Steam coal	0.5
Hard coal	Coking coal	1

### 2.4. Calculation examples

To illustrate the model workflow, two examples are given, both for the case of Germany: the calculation of the actual market share and the model estimate for the same historical year.

Actual energy carrier market shares for the industrial sector in the period 1992–2013 are obtained from Eurostat energy balances (2017). The differentiation between high-temperature and low-temperature processes is based on [Rehfeldt et al., 2017], who present a list of industrial processes and their temperature profile. From these processes, only the energy demand above 500 °C is considered in the fuel switch model. An example data set for the blast furnace process is given in Table 2. The calculation is done as follows: Based on the specific energy consumption (SEC) of 11.64 GJ/t and the production (activity) of 28,872 kt (WorldSteel Association, 2013), the total modeled energy demand in blast furnaces in Germany 2015 is 336 PJ. Due to the assumed temperature profile, 87% of this energy is considered high temperature heat demand. The process “blast furnace” belongs to the industrial subsector iron and steel, with an energy carrier share<sup>2</sup> reported by Eurostat (2017) on the subsector-level of 30% hard coal, 17% natural gas, 20% coke, 15% stack gas and others (Germany, 2012). As a result, the energy demand considered in the fuel switch model consists of 101.0 PJ hard coal, 58.4 PJ natural gas, 68.1 PJ coke, 49.9 PJ stack gas and others. Energy carriers that cannot supply high temperature heat (district heat, solar energy, ambient heat) are excluded. The same is done with all other processes in the respective subsectors (e.g. for iron and steel: coke and sinter production, electric arc furnace, converter and rolling of steel). The sum of these processes is calibrated to statistical top-down values and used as subsectoral energy demand.

The fuel switch model estimates market shares on the subsector level. It starts with a statistical year and calculates the market shares of the next year based on the model parameters and price changes. For Germany in 2012, the calculation for natural gas use in the iron and steel industry is<sup>3</sup>:

<sup>2</sup> Energy carriers are aggregated, e.g. several types of coal products reported by Eurostat belong to “hard coal” and “lignite”.

<sup>3</sup> As the model calibration starts in 1992, all market share values given are model results. The representation includes a small precision loss.

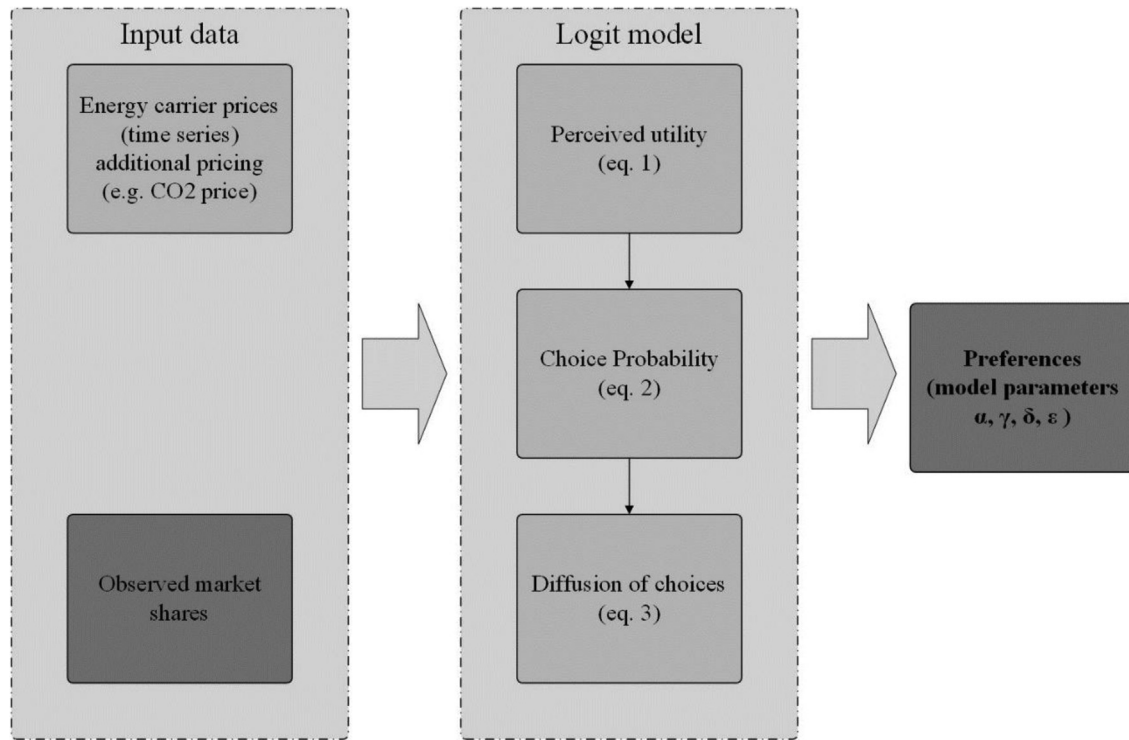


Fig. 3. Workflow during model fit.

**Table 2**  
Process data "blast furnace" (Rehfeldt et al., 2017).

Process	SEC fuels (GJ/t)	Activity Germany 2015 (kt)	<100 °C	100 °C–200 °C	200 °C–500 °C	500 °C–1000 °C	>1000 °C	Based on
Blast furnace	11.64	30,054	0.01	0.01	0.11	0.2	0.67	Arens et al., 2017, WorldSteel Association, 2013, Eurostat, 2017

The market share of natural gas in 2011 is 17.24%. Its price is 11.97 €/GJ, the average price of all considered energy carriers is 11.73 €/GJ. In 2012, the price of natural gas changes to 11.06 €/GJ, the average price changes to 11.87 €/GJ. With the parameters used for natural gas in the German iron and steel subsector (price sensitivity  $\alpha$ : 3, structural factor  $\gamma$ : 9.6, and market homogeneity  $\varepsilon$ : 0.64), Eq. (1) yields an utility of:

$$U_{\text{Natural gas, Iron and steel}} = 0.64 \cdot \left[ -3 \cdot \frac{(11.06 - 11.87)}{11.87} + 9.6 \right] = 6.275$$

The sum all energy carrier's exponential utility (each calculated the same way) is 2,768, thus Eq. (2) yields the choice probability:

$$\pi_{\text{Natural gas, Iron and steel}} = \frac{\exp(6.275)}{2,768} = 19.18 \%$$

With the diffusion function (Eq. (3)) and the diffusion parameter (diffusion factor  $\delta$ : 0.1), the market share is:

$$\text{Share}(\text{Natural gas, Iron and Steel, 2012}) = 17.24 \% + 0.1 \cdot (19.18 \% - 17.24 \%) = 17.43 \%$$

The market share increases because the relative price of natural gas, compared to the alternatives, has decreased. Compared to the choice probability of the same year (19.18%), there still is a

considerable potential for an additional fuel switch. However, this potential is realized over time, given stable price differences.

## 2.5. Process level integration

Based on the process level approach (explained in more detail in Rehfeldt et al., 2017), the price-related market share is modified to represent technological limitations. An example is the minimal required coke use in blast furnaces or the use of process gases in refineries. A certain share of the process' energy demand can be reserved for coke. Thus, only the remaining energy demand is calculated using the economic approach. The same can be done for the maximal use of energy carriers, e.g. low caloric fuels or fuels with limited availability (waste, biomass). As this, as opposed to the economic approach, is based on processes, a higher level of technological detail can be included.

## 3. Results

### 3.1. Revealed preference parameter

The model fit yields parameters that modify the utility of the energy carriers. Without considering a fuel switch, one could assume that the market shares of energy carriers remain constant. The benefit of the model is therefore estimated in a comparison between these constant market shares and the model results. It is

expressed as a coefficient of determination, stating what portion of the difference between the constant average market share and the real development could be explained with the aid of the model. The values given in Table 3 thus do not show how much the model results resemble reality, but how much better the model performs compared to the simple assumption of constant market shares. The coefficient of determination has been calculated according to Eqs. (4)–(6).

$$R^2 = 1 - \frac{SS_{residual}}{SS_{total}} \quad (4)$$

with:

- $SS_{residual}$  the sum of squares of the model
- $SS_{total}$  the sum of squares of the compared model (constant average)

$$SS_{residual} = \sum_{y=1}^n \sum_{i=1}^n (\widehat{MS}_{y,i} - MS_{y,i})^2 \quad (5)$$

with:

**Table 3**  
Coefficients of determination ( $R^2$ ) for the full model compared to constant average energy carrier market shares during the calibration timeframe (1992–2013).

$R^2$	Iron and steel	Non-ferrous metals	Paper and printing	Non-metallic mineral products	Chemical industry	Food, drink and tobacco	Engineering and other metal	Other non-classified	average $R^2$
Austria	<b>0.27</b>	0.82	0.65	0.70	<b>0.26</b>	0.72	0.71	0.79	0.62
Belgium	0.41	0.64	0.81	0.55	0.97	0.90	0.80	0.35	0.68
Bulgaria	0.39	0.56	0.31	0.62	0.46	0.81	0.87	0.71	0.59
Croatia	<b>0.22</b>	0.54	<b>0.24</b>	0.77	0.67	0.89	<b>0.28</b>	0.66	0.53
Czech Republic	<b>0.30</b>	0.58	0.67	0.81	<b>0.20</b>	0.91	0.86	0.35	0.59
Denmark	0.56	-	0.75	0.77	0.80	0.66	0.80	0.76	0.73
Finland	0.60	0.73	0.88	0.86	0.72	0.55	0.92	0.72	0.75
France	<b>0.20</b>	0.78	0.51	0.51	0.47	0.65	0.84	<b>0.15</b>	0.51
Germany	0.64	0.83	0.66	0.64	0.56	0.96	0.88	0.61	0.72
Greece	0.85	0.59	0.89	0.90	0.58	0.82	0.63	0.57	0.73
Hungary	0.61	0.84	0.43	0.70	0.81	0.59	0.72	<b>0.28</b>	0.62
Ireland	-	0.93	<b>0.02</b>	0.40	0.63	0.74	0.79	0.71	0.60
Italy	0.38	0.52	0.64	0.78	0.40	0.35	0.60	0.66	0.54
Latvia	-	<b>0.26</b>	<b>0.14</b>	0.75	0.71	0.87	0.65	0.81	0.60
Lithuania	0.43	-	0.49	0.92	0.46	0.86	0.72	0.86	0.68
Luxembourg	0.84	-	-	0.66	0.84	0.62	-	0.73	0.74
The Netherlands	0.83	0.91	0.50	0.74	0.82	0.69	<b>0.15</b>	0.41	0.63
Poland	<b>0.21</b>	0.67	0.79	0.69	0.57	0.81	0.48	0.53	0.59
Portugal	0.79	0.78	0.91	0.88	0.86	0.85	0.85	0.90	0.85
Romania	0.37	-	0.49	0.72	0.37	0.38	0.32	0.40	0.44
Slovakia	0.57	0.57	0.84	<b>0.27</b>	0.45	0.77	0.84	0.44	0.59
Slovenia	<b>0.17</b>	<b>0.21</b>	0.46	0.57	0.61	0.69	0.56	0.49	0.47
Spain	0.56	0.69	0.76	0.56	0.94	0.82	0.48	0.86	0.71
Sweden	0.66	0.35	0.69	0.49	0.85	0.80	0.63	0.50	0.62
The United Kingdom	0.84	0.79	0.96	0.50	0.82	0.89	0.86	0.51	0.77
average $R^2$	0.51	0.65	0.60	0.67	0.63	0.74	0.68	0.59	0.64

- $\widehat{MS}_{y,i}$  modeled market share of energy carrier  $i$  in year  $y$
- $MS_{y,i}$  actual market share of energy carrier  $i$  in year  $y$

$$SS_{total} = \sum_{y=1}^n \sum_{i=1}^n (\bar{MS}_i - MS_{y,i})^2 \quad (6)$$

with:

- $\bar{MS}_i$  constant average market share of energy carrier  $i$
- $MS_{y,i}$  actual market share of energy carrier  $i$  in year  $y$

An average coefficient of determination of 0.64 can be observed, with notable deviations in individual sectors and countries. In theory, the compared case of a constant average market share is an edge case of the model, and thus the coefficient of determination cannot be negative.<sup>4</sup> However, restricted parameters may cause negative  $R^2$  in small sectors with very volatile behavior. The authors decided to investigate the cases with  $R^2$  below 0.3 (marked bold and darker background in Table 2), finding<sup>5</sup> that there are three major reasons for a low explanatory value:

- Sectors with a small absolute energy demand and/or leaps in it. Among those are:
  - Paper and printing in Ireland ( $R^2$ :0.02); total energy demand was 1.24 PJ in 2004 but dropped to 0.2 PJ in 2012
  - Iron and steel in Croatia (5 PJ in 1992, 0.5 PJ in 2012) and Slovenia (around 3 PJ)
  - Chemical industry Czech Republic (energy demand halved in 2010 from 43 PJ to 22 PJ)
- Sectors in which the compared case of constant average market shares already is a very good fit (i.e. no or little long-term trends exist):
  - Chemical industry in Austria
  - Engineering and other metal in Netherlands (>95% natural gas)
  - Iron and steel in Austria, France, Poland, Norway
- Sectors with (probably<sup>6</sup>) statistical issues
  - Other non-classified in Hungary (no data on light fuel oil use in 2011/12, considerable use before and after)
  - Non-metallic mineral products in Slovakia (virtually no reported waste use between 2000 and 2012, before and after between 4 PJ and 8 PJ)

In Fig. 4, selected combinations of sectors and countries are presented. They are compared qualitatively; Eurostat's (2017) energy balance (left column), constant average market shares in the given time period (middle column) and the model results (right column) from 1992 until 2013. The areas represent market shares of different energy carriers. The above-mentioned case (i) is illustrated for the paper and printing industry in Ireland: The total energy demand halved in 2005, probably due to the closure of a mill. This leads to disruptive market share changes in the energy balance. Due to the diffusion assumptions in the model, it does not follow these changes and consequently creates results close to the base case of constant average market shares. Additionally, historically not observed energy carriers enter the market. This is less likely to influence the results, the more energy demand the

<sup>4</sup> A negative coefficient of determination  $R^2$  would indicate that the model solution has a higher sum of squared errors than the case of a constant average market share. However, this average market share is also inside the solution space of the model. Therefore, when optimizing towards a high  $R^2$ , the model will at least have an  $R^2$  of zero.

<sup>5</sup> Values on the total energy demand in (i) to (iii) are taken from Eurostat (2017).

<sup>6</sup> It can be assumed that reporting methodologies were changed in some instances, especially regarding biomass and waste.

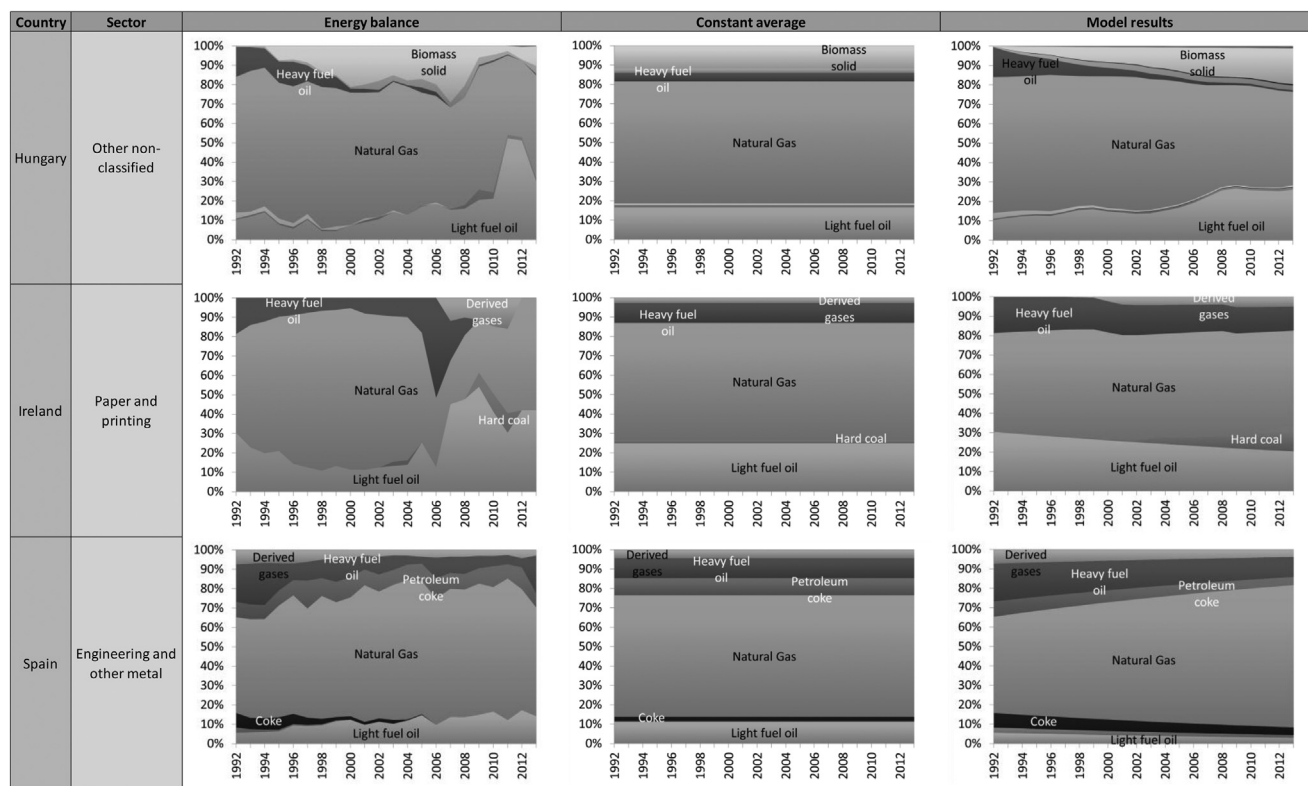


Fig. 4. Comparison of energy balances (Eurostat, 2017), constant average and model results for selected countries and subsectors.

investigated sector represents. Case (ii) is illustrated with the sector “engineering and other metal” in Spain. While natural gas shows some movement, the overall energy carrier shares do not change drastically over the observed period. Thus, the average constant market share already is a good fit. Case (iii) is illustrated using the “other non-classified” industry in Hungary. In 2011, an increase in light fuel use can be observed, with discontinued use in 2013. The model does not follow this development. The other diagrams presented in Fig. 5 show examples of favorable sectors (large energy demand, no disruptive changes during observed period, mix of several energy carriers): iron and steel in Germany, non-metallic minerals in France, chemical industry in The Netherlands.

To address all these cases and capture the long-term trend of the fuel mix in the EU28, countries with low absolute energy demand can be aggregated into groups. This necessarily sacrifices details on those countries (the aggregated parameters cannot be applied to individual countries) but yields more robust parameters since the above mentioned issues impact the model fit much less. Considering the absolute energy demand, individual parameters for the seven biggest energy consumers France, Germany, Italy, The Netherlands, Poland, Spain and The United Kingdom are presented. The other 21 EU member states share aggregated parameters in the results presented here but can (given the mentioned limitations) be calculated individually as well. The parameters are available as supplementary data.

### 3.2. Model validation

The model validation is done similar to the model fit, with the following changes: Instead of using the full data series, only half (1992–2002) is used to fit the model. The model is applied to the other half (2002–2013). The results are compared against the constant market share of 2002, again using the coefficient of

determination. Thus, the validation shows how much better the model describes the fuel share change during 2002 and 2013 compared to the assumption of constant fuel shares (Table 4). For this comparison, both models start with the actual market shares of 2002.<sup>7</sup> Note that next to the seven countries with the highest energy demand in scope, a group “others” is used. It comprises the 23 smallest consumers, which make up for around 32% of the energy demand in scope.

As can be expected, the overall  $R^2$  is lower than the one observed when the whole time series is used as model fit. Additionally, some sectors show negative  $R^2$ . These are caused by disruptive changes similar to those already shown in Fig. 4 (Ireland, Hungary). If they happen during the model fit, the respective energy carrier is overestimated in the second half. If this development stops or reverts, the assumption of a constant market share can yield better results (e.g. United Kingdom, non-metallic minerals (−3.31); Poland, other non-classified (−0.43)). The low  $R^2$  (−0.12) for The Netherlands, non-ferrous metals can be considered less grave, as the total deviation of the modeled from the historic market shares sums to only 6%.<sup>8</sup>

### 3.3. Country and subsector comparison

Whether an energy carrier is favored or avoided in a given country and subsector can be described qualitatively by comparing the two energy carrier-related parameters price sensitivity  $\alpha$  and structural factors  $\gamma$ . An energy carrier has easy market access when

<sup>7</sup> I.e. errors accumulated during model calibration (1992–2002) are removed.

<sup>8</sup> However, the assumption of a constant market share would be a better choice as this particular market shows high dominance of natural gas (>85%) and no trend to change.



**Table 5**

Parameter comparison of selected energy carriers by subsector (higher values marked darker).

Energy carrier	Country averages	Chemical industry	Engineering and other metal	Food, drink and tobacco	Iron and steel	Non-ferrous metals	Non-metallic mineral products	Other non-classified	Paper and printing
Biomass	Alpha	7.63	7.88	6.88	6.50	7.88	7.88	4.63	4.78
	Gamma	-	0.50	1.13	0.38	0.19	0.24	5.02	4.67
Coke	Alpha	3.01	1.68	3.09	3.88	1.10	1.02	2.46	2.67
	Gamma	0.57	1.31	1.67	8.29	3.03	1.26	0.78	0.43
Hard coal	Alpha	1.65	1.53	2.13	4.80	1.68	1.78	2.69	1.91
	Gamma	3.38	2.20	4.23	5.77	2.49	2.29	2.63	3.41
Natural gas	Alpha	2.47	1.18	2.77	2.37	2.11	2.64	3.60	1.96
	Gamma	7.08	9.19	8.85	8.67	9.34	5.15	8.99	7.85
Electricity	Alpha	1.00	1.00	1.00	1.08	1.09	0.25	1.53	1.00
	Gamma	5.38	6.56	6.63	7.88	7.63	2.40	5.75	5.94

**Table 6**

Parameter comparison of selected energy carriers by country (higher values marked darker).

Energy carrier	Subsector averages	Germany	France	Italy	The Netherlands	Poland	Spain	The United Kingdom	Other
Biomass	Alpha	7.63	7.06	7.52	3.89	7.35	6.15	8.63	5.81
	Gamma	2.09	2.31	0.66	0.16	1.83	1.28	0.98	2.82
Coke	Alpha	1.50	1.75	2.79	1.38	5.51	2.13	1.80	2.06
	Gamma	2.46	2.46	1.47	1.33	2.04	2.15	2.17	3.26
Hard coal	Alpha	2.18	2.97	2.72	1.63	1.44	1.98	3.61	1.64
	Gamma	2.74	2.83	1.05	1.57	8.06	1.15	3.68	5.31
Natural gas	Alpha	2.32	2.73	2.63	2.10	1.00	1.27	3.27	3.78
	Gamma	8.98	8.09	7.85	7.96	7.96	7.89	7.21	9.17
Electricity	Alpha	0.89	1.42	0.89	1.04	0.96	0.98	0.89	0.89
	Gamma	6.69	4.82	6.98	4.96	5.85	6.44	6.20	6.23

#### 4. Discussion and conclusion

This paper proposes a discrete choice decision model based on existing knowledge about inter-fuel substitution and industrial high temperature energy demand. It is interpreted according to relevant characteristics of the industrial sector. Among those are an assumed high rationality; heterogeneity, undisclosed (i.e. unknown to the observer) information; inertia through capital stock turnover and inherent preference for some technologies via existing infrastructure and technical restrictions. The model parameters are estimated using a least-squares-fit to historical data of energy carrier prices and market share from 1992 to 2015 for countries in the EU28. Several aspects of the model construction require special attention and discussion: the intended technological explicitness, uncertainty considerations of the used data and the quality of the estimated model parameters.

##### 4.1. Technological explicitness

In order to include information special to high temperature energy demand, (e.g. importance of the fuels caloric value, flue gas treatment and requirements of individual processes), closer investigation of the most relevant processes is necessary. This includes technological limitations both on the process- and fuel-

side. Prominent examples of this are coke use in blast furnaces and temperature dependence of fuel suitability (Beckmann et al., 2003; Davies et al., 2001), e.g. waste and biomass use in clinker production. This can be translated into limits to price sensitivity, which creates a supplementary choice probability for the specified energy carrier in case the calculated choice probability is lower than the given threshold. It reflects the need to use a certain energy carrier regardless of the price, but because of their special, process related properties. There are also other limitations to consider, e.g. exhaust gas-cleaning temperature, fuel composition. These considerations must be included on the process-level and can influence the fuel-switch potential substantially.

Additionally, the decision to switch to another energy carrier does not only depend on fuel prices but also on the costs related to process changes (e.g. new burner, fuel storage, other infrastructure). These costs depend at least on the process and both the old and new energy carrier, additionally the plant level gains importance. In the model presented here, they are considered in the logit parameters in an implicit form. Activity shifts to other processes e.g. towards a combination of direct-reduced iron and electric arc furnaces (DRI/EAF) in the steel industry (Hu and Zhang, 2017) are not included in the fuel switch model. In terms of technological explicitness, this is unsatisfying. However, the model offers the

opportunity to include these dimensions exogenously during scenario definition.

#### 4.2. Uncertainty considerations

The model presented in this paper relies on statistical data on energy demand and prices and technological data from literature. The intended application of the model in a scenario analysis implies inert uncertainty of the results, as they strongly depend on estimations of future developments (industrial activity, fuel prices, policy measures, technological development ...). Considering these elements under deep uncertainty, the uncertainty connected with the used statistical and technological data is assumed to be relatively low. Main concerns regarding the used energy balance (Eurostat, 2017) are the lack of quantifiable uncertainty statements and the possible differences in data quality among countries, as the data is gathered by national institutions. Shortcomings in the available energy balances can have a considerable influence on the model fit, especially the introduction of new energy carrier aggregations during the investigated timeframe. The impact can be mitigated by careful manual calibration<sup>9</sup> and longer time series. Despite several occurrences of inconsistent or implausible statistical data (e.g. Ireland, paper and printing in Fig. 4) the data basis on energy demand is considered to be the best available for the given scope.

It applies to many efforts regarding industrial energy demand that data availability varies not only among countries but also among sectors, which impedes a detailed analysis. Particularly the lack of time series on the temperature level of the energy demand and its respective fuel use increases the uncertainty of projections. As of today, it must be assumed that the results given in Naegler et al. (2015) and Rehfeldt et al. (2017) on temperature distribution of the European industry in 2012 are representable for the industrial structure and therefore have not changed too much over the last twenty years. This is, however, far from certain. The approach to adapt revealed preference parameters taken from total industrial energy demand to high temperature industrial energy demand is thus an approximation. That data availability poses a major challenge especially in the industry sector and on new technologies for both energy efficiency and structural change has already been acknowledged by researchers dealing with bottom-up models, recently Fais et al. (2016). This concerns historic data on demand and costs on a disaggregated level (or even on the top-level of energy balances in some countries) just as much as assumptions on future technologic and economic development. The technological and economic situation can vary on the plant level, while the model works on both the process and subsector level. The conclusions of this paper are therefore not applicable to individual plants but to subsectors and countries.

No price differentiation is made among sectors or company size, as historic data are not available at this level of detail. This can be relevant for natural gas and especially electricity, while world market prices can be assumed adequate for hard coal. Some energy carriers like derived gases are not traded at all on free markets but rather used on-site for power generation or sold directly with no or little transparent pricing. The only clues available on the price in these cases are assumptions on what traded energy carriers might

be replaced or replaceable by them. Existing data gaps are filled via interpolation or analogies with other countries whose development is similar in the observable timeframe. These data imperfections raise concern about the reliability of price-related model responses, especially how much the price model input relates to the price actually perceived by market participants in the individual processes and sectors. As the model works on price differences rather than absolute prices, though, it can be assumed that the price paths represent the real price signals in a qualitative way.

The parameters derived in this paper are based on revealed preferences. Thus, their explanatory value is limited to observed behavior. This limitation is most relevant for energy carriers that have not been present in the industrial sector for a long time or are seldom used. While, for example, natural gas is used in all sectors and countries, biomass is mainly used in the paper industry and to some extent in engineering, food industries, non-metallic minerals and other industries as categorized in Eurostat (2017). Generally, the parameters are assumed to be less certain the less the respective energy carrier has been observed in the past<sup>10</sup>. Additionally, there is the elemental critique on all projections; they rather extended the past than describe the future. This has some foundation in general, but in case of the model presented here, it is of special concern. As the parameters are defined to be constant over time, so are all factors which influence fuel switch that are not explicitly included in the model. While some important policy measures can be included as variables (taxes, levies, subsidies, CO<sub>2</sub>-pricing), the change of not monetarized or not monetizable effects are neglected or so far only treated implicitly. This includes several dimensions identified as being relevant in the context of fuel choice (e.g. health (IPCC, 2014) and security of supply (European Commission, 2014a; b)). Thus, the model assumes that decisions made in the past will be made again in the future (given the same circumstances). This is a limitation of the model. It seems plausible that decision patterns change over time, for example due to policy influence. It is possible to integrate dynamically changing preferences into the model, these can be used in sensitivity analyses and scenario exercises (e.g., what would happen if biomass were perceived like coal?).

#### 4.3. Parameter discussion

The parameters derived from the model fit must have an equivalent in reality in order to be of use in a scenario analysis. They are supposed to address different observations:  $\alpha$  accounts for properties of the individual energy carriers (e.g. stability of combustion, phase, heating value, flue gas composition). As an aggregate, it describes how valuable the energy carrier is perceived in the respective industry and their typical applications. This influences how relevant price differences (both between alternatives and intertemporal) are when evaluating the utility of the energy carrier. Markets that react strongly to price changes will show high values of the price sensitivity  $\alpha$ .<sup>11</sup> The structural factor  $\gamma$  addresses the historic prevalence of energy carriers. It influences the perceived utility independently of the price to account e.g. for existing infrastructure, delivery contracts and long-term technology choice. Price sensitivity  $\alpha$  and the structural factor  $\gamma$  cannot always be

<sup>9</sup> In this regard, manual calibration refers to the adjustment of parameters or input data, where errors or inconsistencies are assumed (see examples given in 3.1). If, for example, in Fig. 4, the spike of fuel oil in 2006 would safely be identified as statistical issue and ignored, the overall result of this country/subsector would improve. However, this detail of analysis is hard to achieve when a large number of countries and subsectors are investigated.

<sup>10</sup> For example, if biomass is not observed in a given subsector, the respective value for  $\gamma$  is likely to be very low. However, whether it is 1 or 2 is irrelevant for the model, as long as it is low enough to generate a low utility. Due to the sigmoid shape of the logit-formulation, very high and very low utilities are much more robust to parameter variations, which in turn means that these parameters derived from the calibration are less certain.

<sup>11</sup> And/or high values of  $\epsilon$ , as they are multiplied. The combination of all parameters has to be considered.

separated, as for example the choice for a furnace type or burner can influence both. The differentiation is easiest for actions that are related to infrastructure, e.g., investments in natural gas access or coal storage should increase the respective structural factor  $\gamma$  but have no influence on the price sensitivity  $\alpha$ .  $\varepsilon$  describes the market homogeneity and therefore transparency. It is high in subsectors with uniform products or process requirements. This parameter also includes soft factors like available information on available technologies and fuels or available capital. Therefore, the market homogeneity  $\varepsilon$  is a measurement for the degree to which the objectively best solution (according to the model) is actually used.<sup>12</sup> Finally, the diffusion factor  $\delta$  describes the inertia of the system. It modifies the speed, with which decisions are implemented. It relates to capital stock turnover and modernization cycles, including short-term (e.g. in multi-fuel burners), medium-term (e.g. modernization of a plant) and long-term fuel switch (e.g. new plants). Subsectors with long investment cycles show lower values (i.e. a lower diffusion speed).

The solution space for the parameters has been restricted. Most of the restrictions are introduced in order to reduce the impact of leaps in historic market share time series that cannot be explained via market-related diffusion and technological considerations (some are mentioned in 3.1).

The restriction of the price sensitivity  $\alpha$  being smaller than  $-1$  is associated to some occurrences of simultaneously rising natural gas prices (both relative and absolute) and market shares in the investigated time series. The resulting price sensitivity would therefore be positive.<sup>13</sup> As this contradicts basic economic theories, it is assumed that unknown factors have influenced the development in this time span. Possible influences are errors or lags in the time series for energy demand and prices, capacity-changes that were planned unrelated to fuel prices or a lag between investment decision and realization. Although this observation hints at model imperfections, it is not uncommon (e.g. Jones, 1995). Especially for electricity and, more important, natural gas, the impact of individual delivery contracts (e.g. with different pricing structures than assumed) cannot be modeled. However, for projections, the assumption of positive price sensitivities would be unsuitable (and inconsistent with the majority of the sectors and countries). It has therefore been assumed that for these special occurrences, price sensitivity is very low, resulting in the need for substantial price shocks to influence the market share.

The diffusion factor  $\delta$  is constrained to values between 0.1 and 1 because a slower diffusion would imply extremely long stock turnover cycles and a lack of short-term fuel-switch options.<sup>14</sup> At the same time, a diffusion factor higher than 1 could potentially destabilize the market share calculation. The restrictions on this parameter and its interpretation require additional research, but model calibrations without restrictions on  $\delta$  showed values between 0.04 and 0.27. The market homogeneity  $\varepsilon$  is limited to be smaller than 10 to reduce the impact of market share leaps in the historic data. These occur in small sectors that are heavily

influenced when plants start or cease operations. In accordance with the theoretical background (long-term fuel-switch), these events are not included in the model. During model calibration, it has been observed that a balanced definition of price sensitivity  $\alpha$  and structural factor  $\gamma$  is very important to create a good model fit to the historical data while retaining price sensitivity for scenario exercises. If this balance is not kept, the model tends towards keeping the status quo (high weight on structural factor  $\gamma$ ). Critically reviewing the parameters proposed so far, one could argue that the potential for a substantial fuel switch is limited. The calculation example (Section 2.4) shows that the price component of the utility calculation makes up for a limited share of the total utility value. Although the logit approach is sensitive to small changes and thus price changes can influence the market share considerably, fundamental shifts (e.g. biomass asserting dominance over natural gas in the non-metallic minerals) are unlikely. While this limitation reflects observed behavior, it must be made transparent in a scenario analysis. In particular, in transformation scenarios, it must be kept in mind that the parameters reflect past preferences that can change in the future.

Lastly, the applied methodology of revealed preference parameters (i.e. preferences observed in the past) performs poorly when trying to evaluate the utility values of energy carriers that were not (or only to a little extent) present in the market during the observed time frame. Potentials tend to be greatly underestimated when the mostly hesitant adoption of new energy carriers is extrapolated into the future. This most prominently applies to the several forms of biomass-based energy and electricity-use for heating. Especially in the context of decarbonisation-scenarios, this is unfortunate as biomass often plays a major role. At the same time, it must be conceded that the methodology to derive model parameters from top-down statistical data does not work well for small sectors (i.e. small number of market participants and low absolute energy demand), since disturbances that are not included in the model (e.g. start or cease of operations) greatly impact market shares of energy carriers. It seems to be beneficial to complement the revealed preferences proposed in this paper with stated preferences that can include future-oriented and hypothetical constellations.

#### 4.4. Further work

As Rivers et al. (2003) and McCollum et al. (2016) point out, heterogeneity among the investigated groups is important for decision models. The model can be improved in this dimension by considering individual processes rather than sectors (e.g. “primary copper production” instead of “non-ferrous metals”) already during the economic model part. This is mainly hindered by data availability regarding individual processes especially regarding economic data (i.e. energy carrier prices) and more detailed energy balances. Ultimately, the plant level must be considered to really capture the heterogeneous industrial structure. Further work on the model must include the quantitative or qualitative support of the parameters derived in this paper. While the model fit strongly suggests that they are suitable to describe the past development adequately, the application in a scenario analysis demands credible argumentation regarding their consistency and plausibility beyond reproducing the past. This requires the implementation of stakeholder expectations and expert knowledge e.g. in the form of stated preferences. To this end, a survey and a series of expert interviews are currently in progress. Additionally, the technical limitations of processes whose implementation is an important benefit of the model should be described in detail.

<sup>12</sup> In model terms, this can be explained by the sigmoid logit-function. When the utility-values are multiplied with a constant factor, the highest utility profits most and increases its market share. Thus, a high market homogeneity  $\varepsilon$  increases the differentiation among alternatives.

<sup>13</sup> As can be seen in Labandeira et al. (2017), price elasticities can be assumed to be negative; though examples of positive values exist in some studies. Although the price sensitivity  $\alpha$  derived here is not a price sensitivity, it behaves as one regarding its sign.

<sup>14</sup> While technical lifetimes of installations of 40 years and more are plausible, maintenance cycles and major revisions offer the opportunity of adjusting the energy use in shorter periods. A  $\delta$  of 0.15 relates to diffusion times of 7–12 years.

## 5. Conclusion

A decision model based on the discrete choice theory that includes market- and technological-driven utility considerations is presented. It describes the energy carrier choice as a combination of consumption preferences and price signals. Inertia of technology stock is modeled using a potential-difference diffusion function. The decision model is included in the bottom-up energy demand simulation model FORECAST (2016) by focusing on sectoral heterogeneity and its impact on the energy carrier and the technology choice. Energy balances and historic price data are used to determine revealed preferences of market participants on the sector level. Long-term trends of energy use are captured with estimated parameters, while short-term effects are neglected or smoothed. This behavior is favorable for scenario analysis and projections, since they usually aim at robust trends and thus use continuous developments of input data (e.g. energy price paths). Therefore, the presented methodology for integration in a bottom-up model and the estimated parameters are well suited for this application. Limitations of the approach (e.g. data requirements) are discussed.

The results show that considerable differences between energy carriers and subsectors can be observed (Section 3.2). They highlight the different market positions of biomass as a (relative) newcomer and natural gas as an established solution in virtually all subsectors and applications: Price advantages (e.g. CO<sub>2</sub>-pricing) are very influential for biomass market penetration and strongly incentivize a fuel switch. At the same time, biomass has to outweigh several benefits of natural gas (e.g. existing infrastructure for transport and use). The dominant role of coal and coke in the steel industry is underlined by the high  $\gamma$  found, especially in countries that rely on blast furnace operations (Poland, United Kingdom, Germany), while Italy as a traditional secondary steel producer shows lower  $\gamma$  for coal.

Due to relatively high prices for electricity (e.g. in Germany, 2013 40 €/GJ compared to an average of all energy carriers of 13 €/GJ), a considerable price reduction is needed to increase its market share. In particular, the price changes observed in the investigated period were not sufficient to have an important impact on the market share. Except for the subsector non-metallic mineral products, high structural values ( $\gamma$ ) for electricity can be observed. They point at applications, in which electricity is used despite its high price (e.g. electric arc furnaces in iron and steel and the chemical industry, production of aluminum in non-ferrous metals). In the context of process heat electrification though, it is questionable whether the derived parameters are able to describe future developments, which are potentially very dynamic.

The validation of the model shows that it yields better results than the immediate assumption of constant market shares in most cases. An average  $R^2$  of 0.45 can be observed during the modeled timeframe (2002–2013) after a calibration period (1992–2002). Coefficients of determination as high as 0.96 can be observed in individual subsectors; on the other hand, negative  $R^2$  are possible in extreme cases. Overall, the model excels at capturing long-term trends in inter-fuel substitution while it is negatively affected by highly dynamic markets and disruptive changes.

## Conflicts of interest

None.

## Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

## Acknowledgements

The authors thank the three anonymous reviewers for their helpful and constructive comments, which greatly improved the paper, as well as Stefan Eidelloth for his continued software development for FORECAST.

## Appendix A. Supplementary data

Supplementary data related to this article can be found at <https://doi.org/10.1016/j.jclepro.2018.03.179>.

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