Energy Strategy Reviews 22 (2018) 237–254

Contents lists available at ScienceDirect

Energy Strategy Reviews

journal homepage: www.elsevier.com/locate/esr

A methodology for bottom-up modelling of energy transitions in the industry sector: The FORECAST model

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ARTICLE INFO

Keywords:
Bottom-up
Industry
Modelling
Energy system analysis
Energy transition

ABSTRACT

Bottom-up energy models can support strategic decision-making and can help to manage an efficient transition to a low-carbon energy system. The manufacturing industry accounted for about 19% of EU-wide greenhouse gas emissions in 2014, which underlines the importance of this sector for model-based decarbonisation assessments.

This paper describes the methodology of the FORECAST model. FORECAST is a bottom-up simulation model used to develop long-term scenarios for the future energy demand of industry, services and household sectors. In this study, we discuss the model in the light of developing transition scenarios for the decarbonisation of the industry sector. In doing so, we focus on the model's structure and simulation algorithms, and provide illustrative results.

The FORECAST model includes a broad range of mitigation options combined with a high level of technological detail. Technology diffusion and stock turnover are explicitly considered to allow insights into transition pathways. The model further includes different policy levers to improve its applicability as a policy support tool. The model is designed to cover the entire industry sector from major energy-intensive processes to the numerous less energy-intensive sub-sectors and applications.

The concluding discussion suggests future research directions to improve the contribution industry sector models can make to supporting the industrial energy transition.

1. Introduction

Energy system models are used as tools to support strategic decision-making in the transition to a low-carbon energy system. While a huge number of diverse models are used today [14], traditionally, energy systems modelling concentrated on the supply side and feature a lower level of technological detail for energy demand sectors. Recently, more diverse simulation-based modelling frameworks have been used that are based on modular approaches with more detailed demand representation [49].

This paper describes the methodology of the FORECAST model. The model develops long-term scenarios for the evolution of energy demand and greenhouse gas (GHG) emissions in the industrial, services and residential sectors of individual countries until 2050. In this paper, we focus on the industry sector module of FORECAST.[1]

The industry sector accounted for about 19% of EU-wide greenhouse gas emissions in 2014. Globally, the importance of the industry sector was even higher, with a 30% share of global GHG emissions in 2010 [20,21]. Compared to other sectors, industry is difficult to decarbonise due to process-specific GHG emissions (e.g. for cement and lime production), high temperature heat demand, feedstock needs and technically required coal use (e.g. oxygen steel production) as well as high technical diversity and international competition.

The chapter on industry in the fifth IPCC assessment report concludes that simply improving energy efficiency will not be sufficient to reduce the absolute global emissions from industry [20,21]. On the contrary, a broad set of mitigation options is needed including fuel and feedstock switching, carbon capture and storage (CCS), material use efficiency, recycling, the re-use of materials and products, product service efficiency and demand reductions. In the following, we briefly review current industry sector models with a particular focus on the types of mitigation options considered.

Bottom-up[2] industry sector models follow different approaches including accounting, simulation and optimisation methods [25]. Some

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[1] When we refer to FORECAST in the following text, we always only mean the industry-related module of FORECAST.
[2] E.g. Ref. [49]: "Bottom-up models are based on a detailed description of the technical components of the energy system".

https://doi.org/10.1016/j.esr.2018.09.005
Received 31 July 2017; Received in revised form 6 August 2018; Accepted 10 September 2018

model-based scenario analyses address the industry sector as a whole [19], while many others focus on individual sub-sectors like steel [44,46] or cement [47] or selected technologies [54,19]; for example, assess long-term GHG reduction scenarios for the UK industry using the TIMES model and consider interactions with the entire UK energy system. The UK model considers incremental energy efficiency improvements for processes but also radical process innovations, fuel switching and CCS. The IEA ETP global scenarios also use an optimisation framework (TIMES) for industry, and focus on individual processes in energy-intensive industries [45]. The model considers energy efficiency, new production processes, fuel and feedstock switching and CCS. The ETP's most ambitious mitigation scenario also considers (exogenous) assumptions about material efficiency along the product value chain. A sector-specific model focusing on steel and cement is presented by Ref. [59]. They model the competition between alternative production technologies, the fuels used, CCS and recycling, with exogenous assumptions about energy efficiency improvements.

The PRIMES model has been used for a variety of scenarios to inform EU decision-making and follows a simulation approach for the industry sector. It considers industry's investment behaviour. Mitigation options include energy efficiency, process switches, fuel and feedstock switches and CCS [13,16]. The US's NEMS model is a simulation model with a high level of technology detail including explicit process flows for energy-intensive industries and less detailed modelling of investment decisions [58]. In NEMS, energy efficiency improvement is a combined result of energy price changes and autonomous improvement. A very detailed bottom-up model used for the Dutch industry sector is described by Ref. [15]. It includes a detailed simulation of micro-economic investment decisions and allows a variety of policy parameters. In terms of mitigation options, it focuses on energy efficiency, fuel switching and combined heat and power, in particular. A similarly detailed approach is followed by the Canadian CIMS model [43].

Other models focus on individual mitigation options or sub-sectors. Examples include assessments of energy efficiency potentials and technologies for steel [10] (Fischedick_et_al_2014) [3,55,57]; and cement [11,30,34,61,63] and chemicals and refineries [35,39] or the cross-cutting potentials of electrification [38]. These assessments are characterised by a very high level of technology detail, often considering individual plants. However, they focus less on endogenous modelling of the transition path or the impact of policy instruments, and more on constructing technology scenarios.

Only a few models consider material use efficiency as a mitigation option [28,45]. If considered at all, this is mostly handled exogenously in the scenario definition, e.g. in the form of reduced industrial production.

Concerning the availability of models to capture the entire set of mitigation options, the IPCC report concludes that: "*The crude representation of materials, products, and demand in scenarios limits the evaluation of the relative importance of material efficiency, product-service efficiency, and demand reduction options.*" [20,21]; p. 744), although these aspects might become more relevant for policy making [62]. Similarly, in a review of 5 integrated assessment models (IAMs) [48], state that "[…] recycling, lightweighting, and other material efficiency strategies should be part of technology-rich IAMs, which would allow them to assess a wider spectrum of emissions mitigation strategies than is currently the case". According to Pauliuk et al., such mitigation options are currently not included in IAMs and most IAMs have a relatively aggregated representation of industrial energy demand. However, a recent publication does take the first steps in this direction and includes more demand-side mitigation options thus reducing the reliance on CCS, for example [60].

The brief literature overview above supports the IPCC's conclusion, particularly for models that aim to cover entire industry sectors. For such models, the high heterogeneity of production technologies and energy uses presents a huge challenge. Some models feature a high level of technology detail, or policy parameters, or consider a transition path or costs, but very few consider all these aspects in an integrated approach. Models with a very high level of technology detail are often less comprehensive in their consideration of policy instruments.

We aim to address this gap by presenting the industry sector bottom-up model FORECAST. The model can address a wide range of research questions, but the main focus of this paper is on the model's ability to calculate comprehensive transition scenarios for the entire industry sector of individual countries by considering a broad scope of mitigation options.

The following description of the FORECAST model focuses on its structure and main simulation algorithms as of December 2017. Due to the model's broad scope and long history in applied policy support, it is only possible to provide an overview of the model in this article. We refer the reader to other publications for more detailed descriptions of individual sub-models or applications to individual research questions.

This paper continues with a brief summary of the model's development and application history and a general overview of its structure. A more detailed discussion of the six individual sub-models follows, and a brief summary of model interfaces and add-ons, before the description of an illustrative case study. Finally, we draw general conclusions and make recommendations. We illustrate the individual sections with exemplary results from different studies. The article is accompanied by supplementary online material that completes the model description with tables on technology structure and input parameters.

2. Model history

The FORECAST model has been undergoing development for more than 10 years. A brief overview of important industry-related studies also provides insights into the typical research questions addressed by the model. Early studies looked at energy efficiency potentials and costs in Germany's basic materials industries [22,24,25] as well as in the EU as a whole [17]. The model has been extended continuously from its origins as an accounting model focusing on technology scenarios into a simulation model capable of assessing the impact of policies. Such studies included assessments of energy efficiency policies and their contribution to EU-targets in 2020 and 2030 for the European Commission [27] as well as long-term climate policy scenarios for the German Environment Agency (Schlomann_et_al_2011). Links with macro-economic models and considering the circular economy have been other topics in the model's development [33]. Recent applications have widened the scope of the model to include fuel switching for process heating and space heating, allowing the assessment of the entire heating and cooling demand and supply [6]. With an even broader scope and embedded in an overall energy system transition study [50], the model has also been used to develop a decarbonisation pathway for the entire industry sector in Germany [23]. This study is presented in the illustrative example in section 6.

While the FORECAST model has also been used for international studies (e.g. the cement industry in Taiwan [34], or Brazil), most applications have a clear focus on Germany and the EU. Most of the studies looked at the years 2030 and 2050. In principle, however, short-term analyses and ex-post analyses are also possible. One example of an ex-post analysis is the development of end-use energy balances for the EU heating and cooling sector [51].

3. Model overview

The FORECAST model is designed as a tool that can be used to support strategic decisions. Its main objective is to develop scenarios for the long-term development of energy demand and greenhouse gas emissions for the industry, services and household sectors of entire countries. The industry sector module of FORECAST considers a broad range of mitigation options combined with a high level of technological detail. Technology diffusion and stock turnover are explicitly considered to allow insights into transition pathways and speed. The model further aims to integrate policies and considers changes in the socio-economic framework.

3.1. Scope

The model is designed to cover the entire industry sector including major energy-intensive processes with a high level of detail, but also many less energy-intensive sub-sectors and applications (see annex Table 4 for a complete list of processes). The complete simulation is conducted on the level of individual sub-sectors like iron and steel. The scope of the model is defined by the energy balances and focuses on final energy, but also includes useful energy.[3]

3.2. Research questions

The model can address various research questions related to industrial energy demand and GHG emissions in the context of technical change. Examples include scenarios for the future demand of individual energy carriers like electricity or natural gas, calculations of energy saving potentials and their impact on GHG emissions, abatement cost curves, ex-ante or ex-post policy impact assessments and low-carbon transition scenarios.

3.3. Structure

The structure of FORECAST also reflects the heterogeneity and data availability in the industry sector. Energy-intensive processes are considered explicitly, while other technologies and energy-using equipment are considered in the form of cross-cutting technologies modelled similarly across all sub-sectors. Accordingly, the model is divided into sub-models.

Fig. 1 shows the structure of FORECAST. Six sub-models are distinguished: *macro, energy-intensive processes, space heating and cooling, electric motors and lighting, furnaces, and steam and hot water*. Add-ons are also defined that can be applied after calculation of the core model. Different approaches to simulate technology change are used in the various sub-models. These range from exogenous assumptions, diffusion curves to vintage stock models and discrete choice simulation. The importance of each sub-model in terms of final energy demand is illustrated in Fig. 2, which distributes the entire EU industry final energy demand of about 3020 TWh in 2015 to the individual sub-models and sub-sectors.

3.4. Input parameters

Input data comprise the main drivers, policy parameters, structural information and a huge set of technology parameters including behavioural assumptions (see Fig. 1). Most of these input parameters are long-term drivers of energy demand and GHG emissions, but business cycles and temperature (heating degree days) are included as well since these can affect energy demand in a one-year horizon.

3.5. Policies and investment decisions

FORECAST allows the simulation of policy impacts. This includes price-based policies like subsidies or taxes, market-based instruments like the EU's Emissions Trading Scheme, but also standards like minimum energy performance standards for individual products. In a more aggregated form, policy instruments such as energy management or audits schemes are also considered by adjusting behaviour parameters.

The need to simulate the impact of policies also requires detailed representation of investment decisions in the model, because these are the main anchor for policy intervention. They include investments in new steam generation technology, energy efficiency improvements in existing installations, new electric motors but also investments in radically new production plants. Investment decisions in energy efficiency are modelled according to the real-life behaviour of companies, which often deviates from cost-optimal decisions under perfect knowledge and faces manifold barriers [25]. Instead, investment decisions are myopic (based on costs and prices in a specific year) and simplified decision rules are applied (like payback time threshold).

3.6. Mitigation options and technology detail

Achieving deep decarbonisation in 2050 requires a broad range of mitigation options. FORECAST considers the following mitigation options.

- energy efficiency (incremental and radical change)
- fuel switching (to renewable and low-carbon energy carriers)
- carbon capture and storage (CCS)
- circular economy and recycling
- material efficiency and substitution down the value chain.

These mitigation options are included with a varying level of detail in the individual sub-models as discussed below. Energy efficiency improvements and fuel switching are modelled endogenously on a technology level in a number of individual sub-models. Mitigation options like material efficiency and recycling are considered via exogenous assumptions that need to be incorporated in the scenario definition.

Fig. 3 gives an overview of the technology detail included in FORECAST. For a complete list of all the technologies included in FORECAST, we refer to the supplementary online material.

3.7. Results

The main results of the FORECAST model are time series of final and useful energy demand and the related GHG emissions with a high level of disaggregation regarding energy carriers, sub-sectors, end-uses and technologies (see Fig. 4). The results are presented as annual values by country and scenario. However, model add-ons allow a more detailed disaggregation to NUTS3 regions and an hourly resolution (see section 5). Various cost categories including capital expenditures, operating costs, energy costs and policy programme costs are also provided for all parts of the model where technology-explicit modelling is done. Furthermore, the interim results can be assessed at all levels of detail to illustrate the underlying technology change (e.g. a time series of the market share for steam generation technologies).

3.8. Software implementation

The FORECAST model is written in the programming language Visual Basic.NET and requires installation of the Microsoft.net framework. Data is stored in local SQLite databases. Model running times vary according to the time horizon, number of countries and number of scenarios selected. Calculating one scenario for one country currently takes about 30 min on an ordinary laptop computer. Depending on the computer used, parallel calculation of multiple scenarios and countries is possible and can reduce running times considerably for, e.g. EU-wide scenarios.

4. Model core: methodology by sub-model

The following presentation of the individual sub-models only

[3] Parts of the transformation sector are included in some studies, in particular, industrial CHP, refineries and coke ovens, although they are not included in the final energy definitions of energy balances.

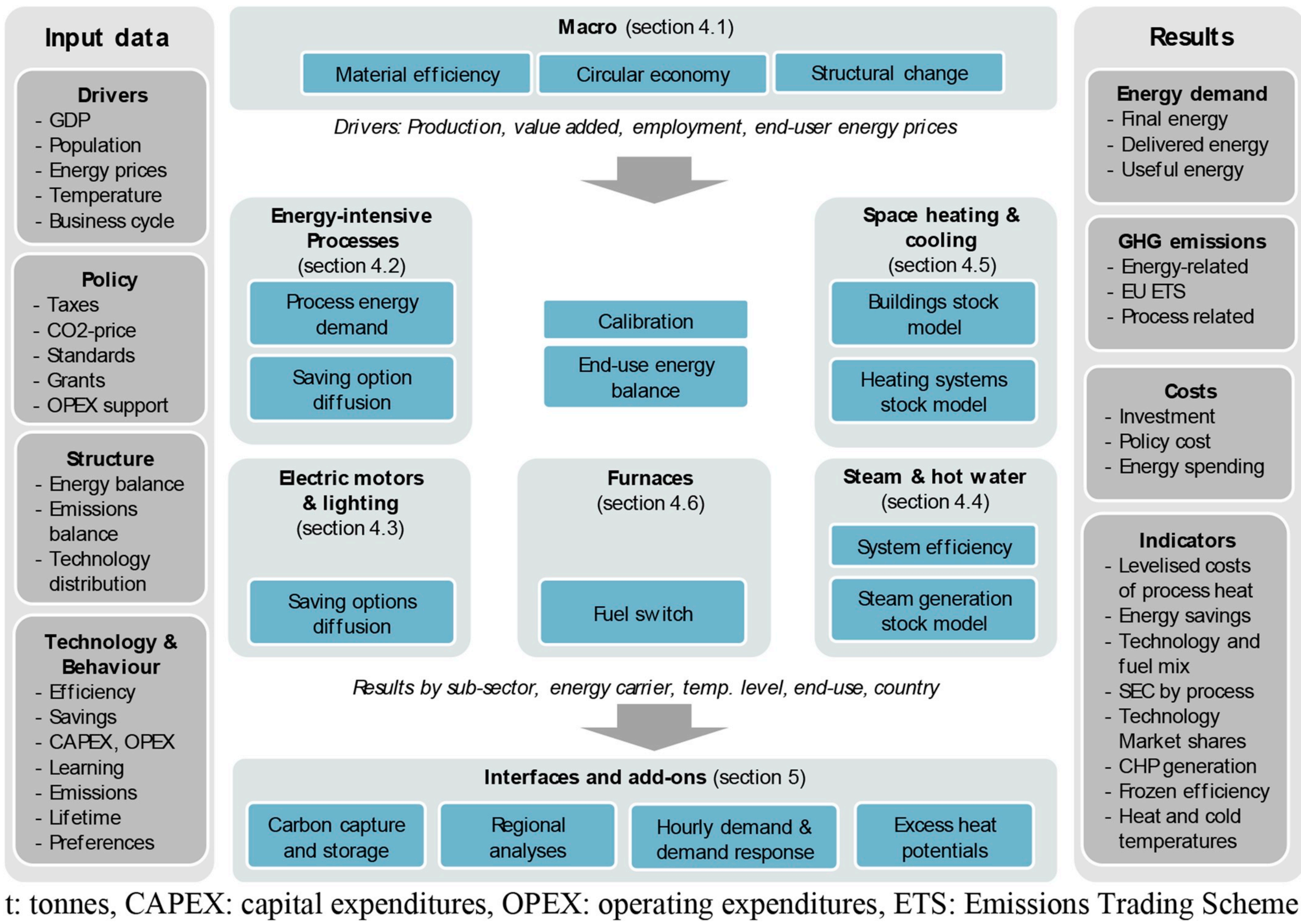

Fig. 1. Overview of the FORECAST model: Input data, methods and sub-models.

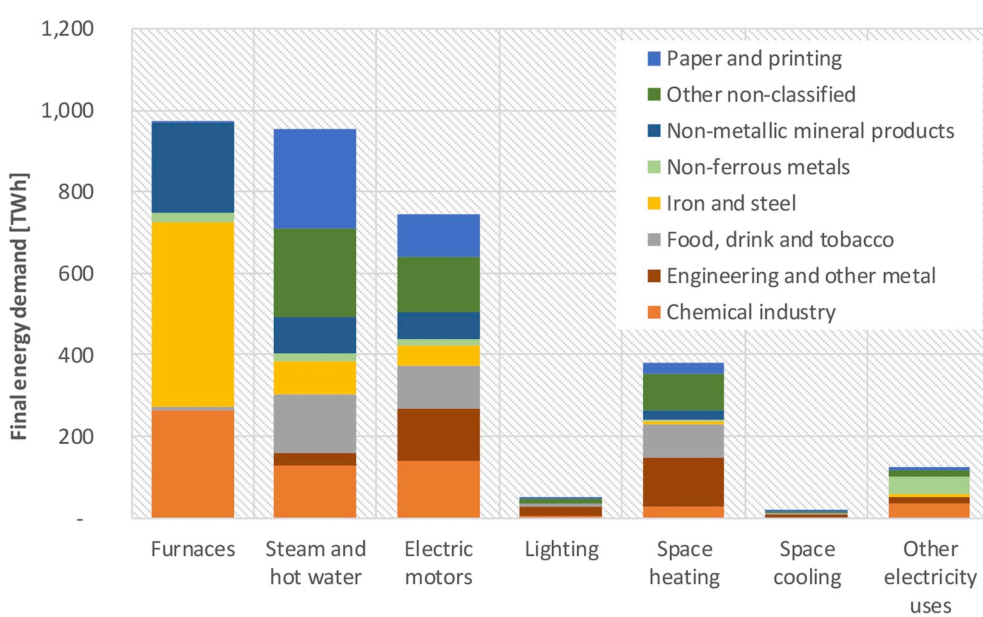

Fig. 2. EU28 industrial final energy demand in 2015 by end-use and sub-sector. The figure shows an end-use oriented distribution of final energy demand. Energy-intensive processes are not shown individually, but allocated to individual energy end-uses.

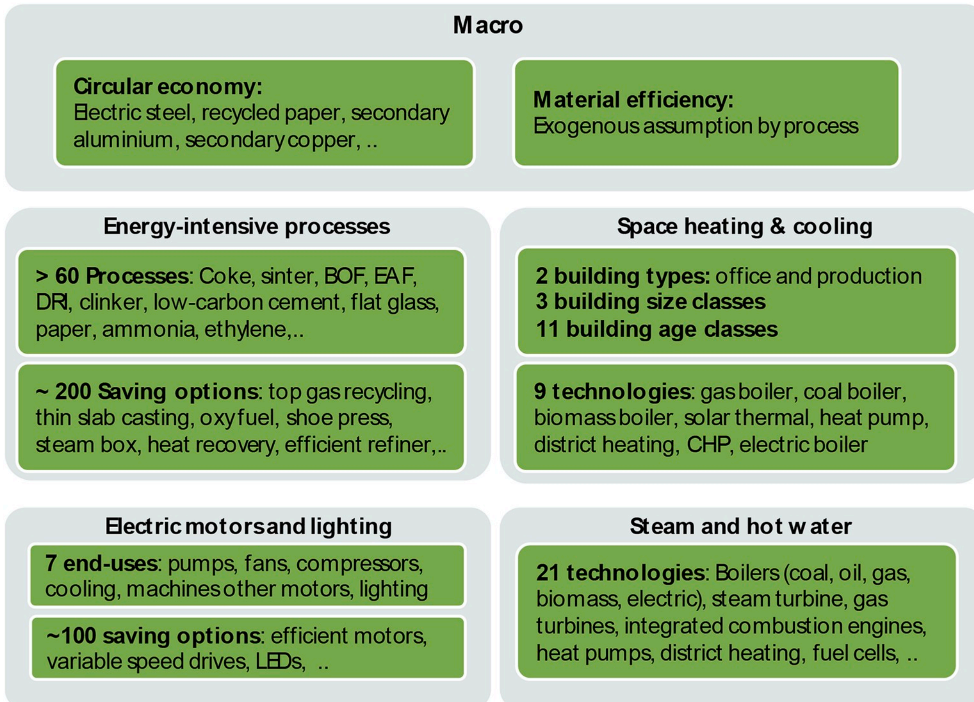

Fig. 3. Overview of technology detail in FORECAST by sub-model.

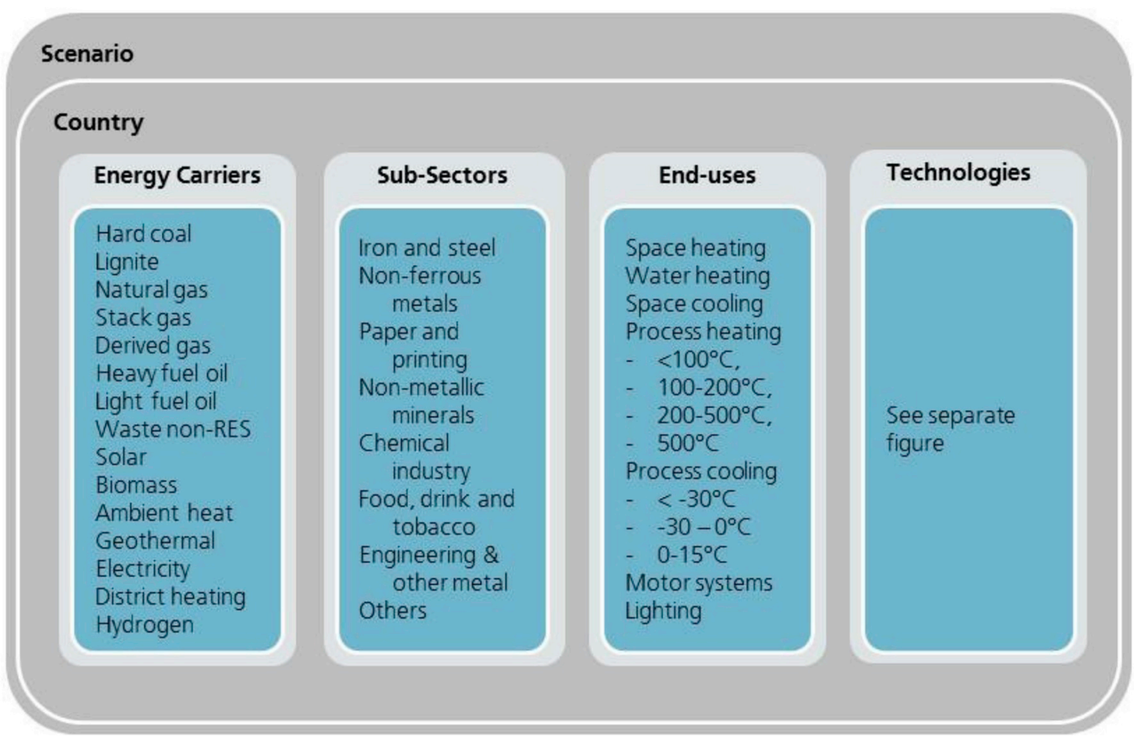

Fig. 4. Level of disaggregation of FORECAST results.

focuses on their key characteristics. Most of the sub-models comprise thousands of lines of programming code. To give the reader a deeper understanding of the individual sub-models, we refer to additional literature that presents individual parts of the model in each of the sections. In the following, we first describe the structure of the sub-model and then the main elements of the simulation approach including key formulas. Different methods are used across the individual sub-models to reflect the heterogeneity and data availability in the respective areas. For example, the *energy-intensive processes sub-model* uses a simplified diffusion model to reflect the large variety of different technologies, while the *steam and hot water sub-model* is based on a detailed vintage stock model that distinguishes the age of the technology stock. In order

Table 1
Summary of main methods used and further reading for each sub-model.

Sub-model	Main method used	Further reading and material
Macro	Econometric, material flow modelling and exogenous scenario definition	Macro-economic framework [31]: Material efficiency and circular economy: [32] [33];
Energy-intensive processes	Simplified technology diffusion	Method [22]: Technology assumptions [24]: Bottom-up energy balance [51]:
Electric motors and lighting	Simplified technology diffusion	–
Steam and hot water	Vintage stock model plus discrete choice	[6]
Space heating and cooling	Vintage stock model plus discrete choice	[7]
Furnaces	Simplified discrete choice	[52]

to avoid unnecessary repetition in the following model description, we only describe key methodological approaches once (e.g. the vintage stock approach is described in the *steam and hot water sub-model*, but not in the *space heating and cooling sub-model*). Table 1 summarizes the main methods used and further reading for each sub-model. More published reports and papers are described in section 2.

Besides the indicated available publications and the annex of this document, further documentation is available in the supplementary online material. This includes, e.g. lists of all the technologies included and lists of all input parameters by sub-model.

4.1. Sub-model macro

This module translates general macroeconomic drivers such as GDP, the population or wholesale energy prices into more specific demand drivers, such as industrial production in tonnes by process or end-user energy prices that are taken up by the subsequent sub-models. The following section describes how future projections for industrial production are estimated considering material strategies (i.e. material efficiency and circular economy). A more detailed description can be found in Refs. [32] and [31].

The future development of production output by process (in physical units) is a central driver of energy consumption in the (basic materials) industry, in particular as production is much more closely related to energy demand than economic drivers such as the value added. As mentioned before, FORECAST considers more than 60 individual processes and their respective products and semi-products measured in tonnes of output (see annex Table 4). This detailed representation of the industry sector at product and process level allows the consideration of specific trends and assumptions concerning material efficiency, the circular economy, the downstream demand for products, saturation effects and structural changes within sub-sectors.

In general, four main groups of products are distinguished [33]:

- basic bulk products (e.g. ethylene, chlorine, etc.),
- basic bulk products with primary and secondary production route (e.g. crude steel, aluminium),
- basic products made from raw materials with auxiliary and additive materials (e.g. paper using chemical and mechanical pulp paper with fillers and bleaching additives),
- products from basic materials or basic products (e.g. glass, ceramics, rolled steel).

Three steps are undertaken to develop production projections for each product and semi-product.

1. Depending on the characteristics of each product, the main drivers are identified and selected (e.g. per capita demand, gross value added, changing recycling and scrap rates, trends towards accompanying services).
2. Domestic demand and foreign trade developments are estimated depending on the drivers chosen in step one (e.g. per capita demand including saturation effects or the relation of domestic direct demand to gross value added of related and subsequent industries) and the overarching scenario assumptions (e.g. energy carrier prices).
3. Product specific effects are considered, e.g. intensity of material strategies including the circular economy and material efficiency.

As an example, the secondary crude steel production route (electric arc furnace based on scrap and electricity) is many times less energy- and CO_2-intensive than primary production (basic oxygen furnace: based on iron ore and coal). In the past, the European steel industry continuously increased the share of scrap-based secondary steel, which has led to significant energy savings in the sector [4].

However, the potential for continued additional substitution of primary steel by secondary steel depends on a variety of different factors such as future scrap availability and scrap quality as well as various material strategies that reduce end-of-life scrap occurrence and the true steel use of a country. Table 2 shows exemplarily a list of elements included in FORECAST for the case of the steel industry.

Analyses show that material strategies like material efficiency (e.g. use of thinner sheets due to improved material properties - high strength steel), substitution (e.g. vehicle construction using aluminium or carbon-fibre-reinforced plastics) and changes in behaviour (e.g. car sharing/pooling but also longer usage of steel containing products) can lead to an additional reduction in the energy demand of the steel industry [33].

4.2. Sub-model energy-intensive processes

4.2.1. Structure of sub-model

The *energy-intensive processes* sub-model constructs the bottom-up structure for the basic materials industries based on detailed production data projections from the *macro* sub-model for more than 60 individual processes. Further, it simulates the diffusion of saving options that improve the energy efficiency of respective processes and/or reduce process-related emissions.

The sub-model is based on the hierarchical structure presented in Fig. 5. For each country, the highest level of aggregation is industry as a whole. According to the sectoral definition used in the Eurostat (or national) energy balances, industry is divided into different sub-sectors like iron and steel or pulp and paper. On the level below the sub-sectors, individual processes (see Table 4) are defined that represent major (semi-) products or production processes (e.g. steel finishing or mechanical pulping). Saving options are defined for each process (full list available in online material).

For process-specific technologies, the main driver is the projection of the physical production of defined processes (e.g. tons of crude steel from blast furnaces). Depending on data availability, processes can consist of individual production steps (e.g. burning of clinker in the cement industry) or entire production lines for individual products or product groups (e.g. production of paper).

Table 2
Elements in modelling material strategies considered for the example of the steel industry.
Source: [33], based on [1,2,41,42].

Element	Category	Description	Implementation in the model	Selected examples
Value added ratio	Trends to higher gross value added	Decoupling of value creation and steel consumption through product-related services.	Reduces apparent steel use	Maintenance and project management
Scrap rates	Fabrication/forming improvements	Improvements in production that lead to lower fabrication and forming losses.	Reduces losses (= > demand) & future scrap availability	Near-net-shape casting, improved measurement technologies
Material efficiency potentials	Material strategy improvements	Improvements in product design that lead to lower steel consumption	Reduces true steel use	Improved material properties: high quality/strength steel products
Material substitution potentials	Material strategy improvements	Substitution in downstream value chain that leads to lower steel consumption	Reduces true steel use	Use of aluminium, carbon fibre, magnesium in vehicle construction
More intense use potentials	Material strategy improvements	User behaviour changes leading to lower steel consumption	Reduces true steel use	Car sharing, pooling
Res-use potentials	Material strategy improvements	User behaviour changes leading to lower steel consumption	Reduces end-of-life scrap & future scrap availability	Export of steel-containing products at the end of their lifetime
End-of-life recycling rates	Circular economy	Improvements in scrap composition and recycling/sorting technologies.	Increases end-of-life scrap & future scrap availability	New sorting technologies, digitalisation
Average time of usage	Circular economy	Changes in average lifetime of steel-containing products	Reduces end-of-life scrap & future scrap availability	Turning away from the throw-away society

Apparent steel use: Domestic steel deliveries plus net direct imports; true steel use: Apparent steel use minus net indirect steel imports (e.g. cars).

4.2.2. Simulation algorithm for saving option diffusion

The energy demand of a process is broken down into individual energy carriers based on the energy carrier shares of the sub-sector to which the process is allocated (in case the energy mix is not defined manually).

The resulting energy demand of a process (ED) is calculated as the reference specific energy consumption (SEC) multiplied by the industrial production (IP) and corrected for the sum of total energy savings (ES).

$$ED_{p,t} = IP_{t,p} * \left(SEC_{t=StartYear,p} - \sum_{SO=1}^{n} ES_{t,p,SO}\right) \tag{1}$$

With: t = year, p = process, SO = saving option.

The high number of processes considered in FORECAST allows technical energy saving options to be defined very specifically. Further, adjusting production assumptions of individual processes is one way to consider structural changes from shifts among products/processes driven by the circular economy or material efficiency strategies (see *macro* sub-model).

This sub-model maps technological change via the diffusion of saving options (and exogenous shifts among processes). Saving options can be small incremental improvements in existing technologies as well as radically new production processes. Each saving option is allocated to a process. With increasing market diffusion, saving options reduce the SEC of the processes. In a few cases, they can also reduce the specific process-related greenhouse gas (GHG) emissions. FORECAST currently considers about 200 saving options. Due to the high degree of heterogeneity and diversity as well as low data availability, the diffusion of saving options is simulated based on a simplified model that follows S-shaped diffusion curves and takes profitability into account, but is not based on a detailed vintage stock approach or technology competition models.

The simulation of saving options is described briefly below. For a more detailed description, see Ref. [22].

The diffusion of saving options is determined by their payback period and diffusion boundaries. The minimum, maximum and resulting cost-effective diffusion are shown in Fig. 6. Minimum diffusion represents a path in which the autonomous replacement of capital stock results in slowly increasing efficiency. It is not cost-driven. Maximum diffusion, on the other hand, represents the fastest market diffusion that is achievable without premature replacement of capital stock (before end-of-life).

The payback (PBT) time is calculated as follows for saving option SO, year t and country c.

$$PBT_{so,c,t} = \frac{C^{I}_{t,so}}{C^{E}_{t,so,c} + C^{EUA}_{t,so,c} - C^{R}_{t,so}} \tag{2}$$

With:

C_I: Initial investment cost (CAPEX)
C_E: Energy cost savings:
C_{EUA}: EU allowance cost savings
C_R: Running cost of mitigation option (OPEX)

In order to consider heterogeneity among companies (different levels of energy efficiency, different energy prices, etc.), a distribution of payback time expectations is used: With increasing payback time, the share of companies investing decreases. Consequently, a very short payback time results in a diffusion rate close to the maximum diffusion, and a very long payback time results in low diffusion close to minimum diffusion. This is reflected in the following formula following a logistic growth model:

$$f(PB) = 1 - \frac{N}{1 + \frac{N - f(0)}{f(0)} e^{-PB\beta}} \tag{3}$$

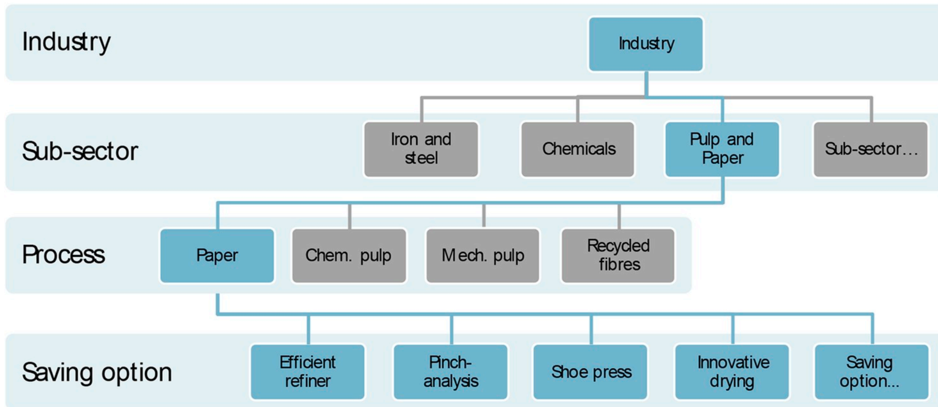

Fig. 5. Hierarchical structure of FORECAST model (the exemplary line for paper production is highlighted in blue).

With:

N: Maximum market share (typically = 1)
PB: Payback time of saving option
f(0): Start value for share of technical diffusion for PB = 0
β: Logistic beta coefficient

Results are between 0 and 1, where 1 means that the resulting cost-effective diffusion equals the maximum diffusion. To illustrate this, Fig. 7 shows two exemplary scenario definitions where the parameters β and N are varied to reflect differences in the payback time expectations of companies. For the current policy scenario, saving options with 3 years payback time are implemented in about 55% of cases, while this figure rises to about 85% in the transformation scenario.

The resulting cost-effective diffusion is then calculated by starting from the minimum diffusion. Then, the difference between the maximum diffusion and the minimum diffusion multiplied by the result of equation (3) is added on top. Consequently, the cost-effective diffusion ranges between the minimum and the maximum diffusion.

Finally, the annual energy savings (ES) for each saving option in year t for one scenario (Sc) are calculated based on the specific saving potential (sp), the diffusion (Diff) of the saving option in year t and the industrial production (IP) of the related process (p).

$$ES_{t,p,SO} = sp_{SO} * (Diff_{t,SO} - Diff_{t=StartYear,SO}) * IP_{t,p} \tag{4}$$

The effect of energy savings is then considered in the overall assessment as described in equation (1).

Fig. 8 shows an exemplary assessment of saving options in the form of abatement cost curves. Such curves are commonly used as decision support tools to make the results of CO_2 abatement or energy efficiency and costs more transparent.

4.3. Sub-model electric motors and lighting

Although electric motors and lighting are usually smaller than process-specific technologies, the numbers involved are huge due to their widespread application. This means they account for an immense share of industrial electricity consumption, more than 70% in many countries. They are grouped under the term cross-cutting technologies (CCT), implemented in the model as a share of the process's electricity consumption, and their main driver is the projected development of production by process (and value added by subsector).

FORECAST considers seven CCTs: compressors, pumps, cold appliances, fans, machine tools, other motors and lighting. Saving options for CCTs follow a similar concept as the saving options for processes (see section 4.2). Each saving option is allocated to a CCT and improves energy efficiency with increasing diffusion. Saving option examples include IE3 motors, variable speed drives, high efficiency pumps, optimised ducting (see supplementary online material for the complete list).

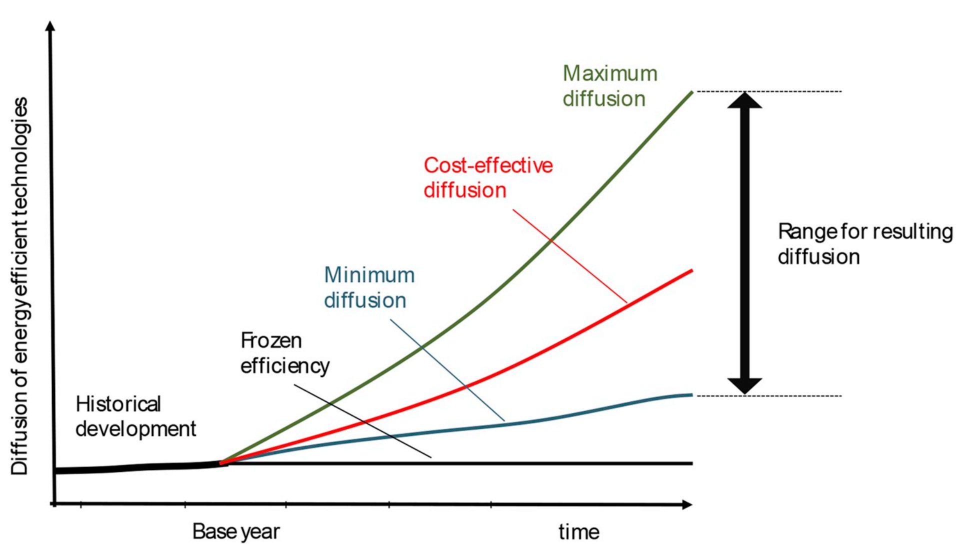

Fig. 6. Schematic representation of saving option diffusion in the sub-models *energy-intensive processes and electric motors and lighting*.

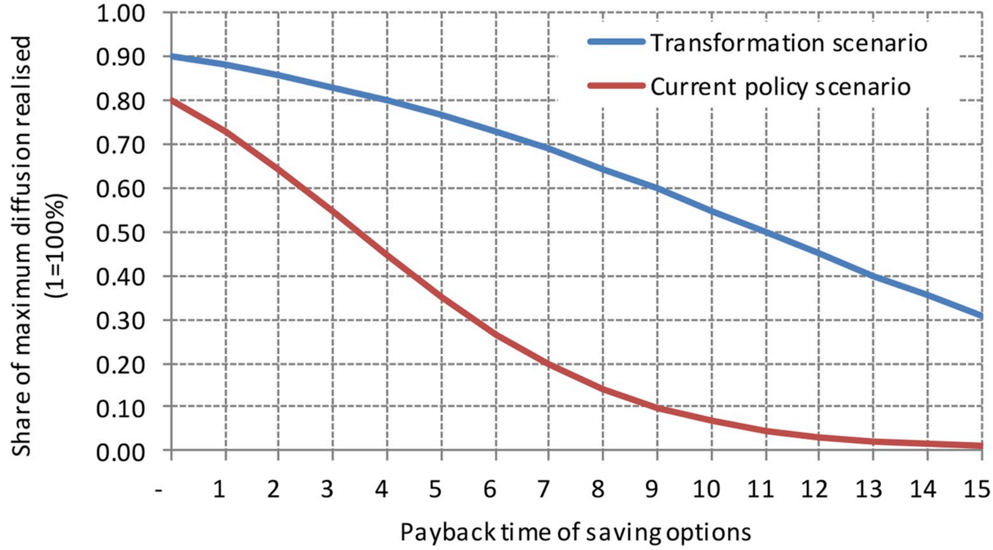

Fig. 7. Exemplary calculation of cost-effective diffusion values (implementation share of maximum diffusion) for two scenarios (transformation: β = 0.2 and N = 0.9; current policy scenario: β = 0.4 and N = 0.8).

4.4. Sub-model steam and hot water

4.4.1. Structure of sub-model

Steam and hot water generation (in short "steam") accounts for about one quarter of industrial final energy demand in many countries. Steam is needed in most industrial sub-sectors, but its potential generation technologies are quite comparable, so they are treated as a homogenous group of technologies in FORECAST. The corresponding sub-model comprises both the distribution of steam and its generation.

For the modelling, we distinguish steam distribution (pipes) and steam generation. As only limited empirical information is available about the performance of existing steam distribution systems, we assume exogenous efficiency improvement rates based on the scarce literature available [17].

Steam generation, on the other hand, is modelled based on a detailed bottom-up vintage stock model simulating the turnover and competition of steam generation technologies. The available generation technologies range from simple boilers, through small and medium-sized internal combustion engines to large-scale gas and steam turbines. Low-temperature options like heat pumps, solar thermal and district heating are also included (Table 3). Distinguishing steam and hot water demand into three temperature ranges (< 100, 100–200 and 200–500) restricts the use of low-temperature options to the range < 100 °C.

4.4.2. Simulation algorithm for technology stock change

Fig. 9 shows an overview of the simulation for steam generation capacity and market shares. The work can be divided into two major steps: (1) calculation of technology choice, and (2) the construction of the installation stock and its turnover.

4.4.2.1. Technology choice. To simulate the technology choice for new steam generation installations, first, the availability of technologies is

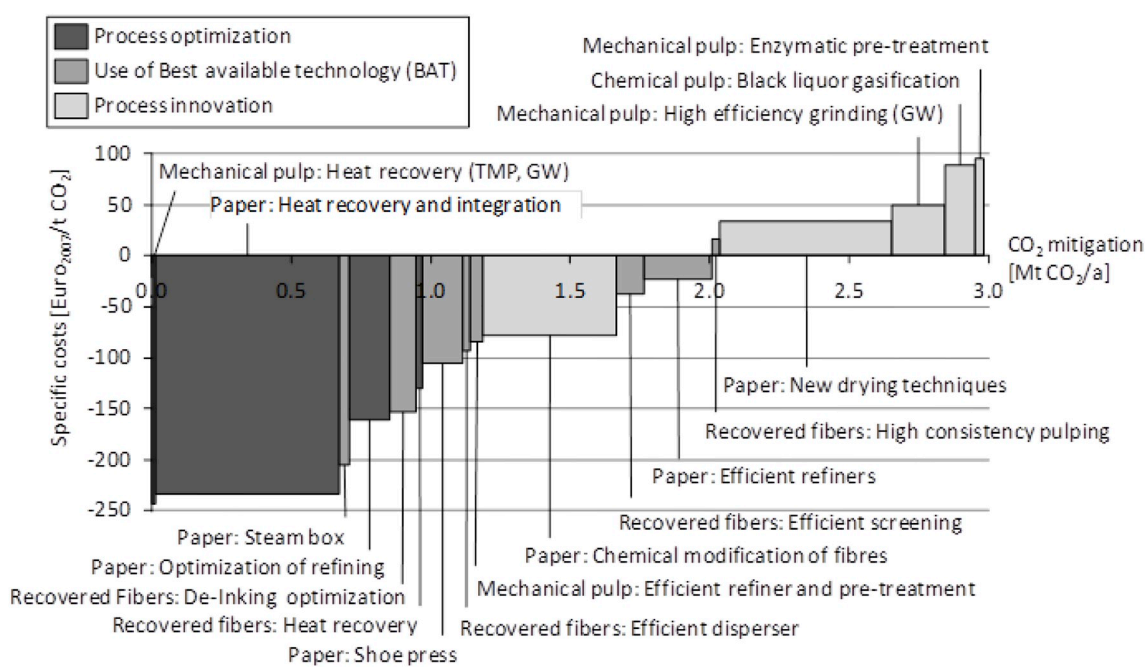

Fig. 8. Exemplary CO_2 abatement cost curve based on saving options for the pulp and paper industry in Germany [22].

Table 3
Steam and hot water generation technologies included in FORECAST.

Technology	CHP	Energy carrier
Internal combustion engine	Yes	Natural gas
Internal combustion engine	Yes	Liquid biofuels
Internal combustion engine	Yes	Light fuel oil
Gas turbine	Yes	Natural gas, process gases
Steam turbine	Yes	Light fuel oil
Steam turbine	Yes	Biomass
Steam turbine	Yes	Natural gas
Steam turbine	Yes	Hard coal
Steam turbine	Yes	Waste
Combined cycle gas turbine	Yes	Natural gas, process gases
Fuel cell	Yes	Natural gas
Boiler	No	Natural gas
Boiler	No	Hard coal
Boiler	No	Light fuel oil
Boiler	No	Biomass
Boiler	No	Other
Boiler	No	Waste
Boiler	No	Electricity
District heat	No	–
Heat pump sorption	No	Natural gas, other
Heat pump compression	No	Electricity

checked. This may depend on regulations (e.g. ban on certain energy carriers or technologies) and a combination of installation and company size (e.g. company energy demand too low to reach necessary full load hours of a steam turbine). Subsequently, the steam generation costs of the available technologies are assessed, taking into account their investment, operation and maintenance costs, energy costs, the CO_2 price and potential subsidies and revenues (e.g. electricity generation in CHP-installations). Base load (e.g. internal combustion engine) and peak load technologies (e.g. gas boiler) are distinguished by their expected full load operating hours [56]. As an intermediate result, the available technologies can be ranked by their specific steam generation costs, which indicate their attractiveness.

However, experience shows that generation costs alone cannot explain the actual market shares observed in the past. "Cheaper" technologies usually capture higher market shares, but more expensive technologies also achieve substantial market shares, which shows that additional non-monetary factors play an important role (i.e. the technology is perceived as having a higher utility than the economic data would suggest). These factors are partly included in the formula or more indirectly via the parameter λ (see stock model below), which defines how heterogeneous (many niches) or homogeneous (one dominant technology) the market is [53]. Equation (5) shows the calculation of perceived costs by technology. This modified cost structure defines the final technology choice.

$$U_{t,\,c,y} = ASC_{t,\,c} * [I_{t,c,y} + OM_{t,c,y} + E_{t,c,y} + P_{t,c,y} + R_{t,c,y}] \quad (5)$$

With:

$U_{t,\,c,y}$: Perceived costs
$ASC_{t,\,c}$: Alternative specific constant
$I_{t,c,y}$: Annualized investment
$OM_{t,c,y}$: Operating and maintenance cost
$E_{t,c,y}$: Energy costs
$P_{t,c,y}$: Policy-induced costs or revenues (e.g. subsidies)
$R_{t,c,y}$: Additional revenues
Indices: Technology t, country c, year y

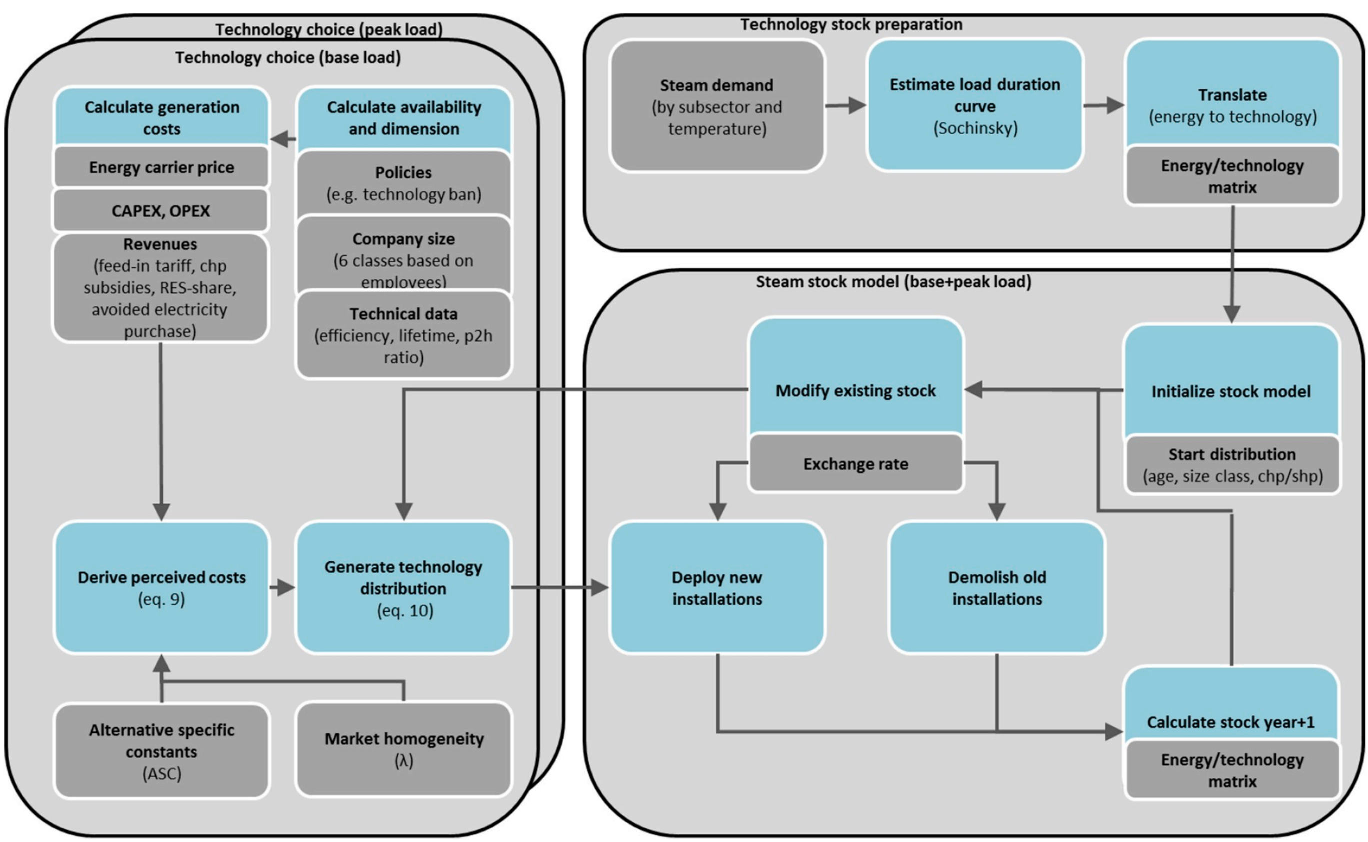

Fig. 9. Simplified calculation steps for steam generation technology choice and stock turnover.

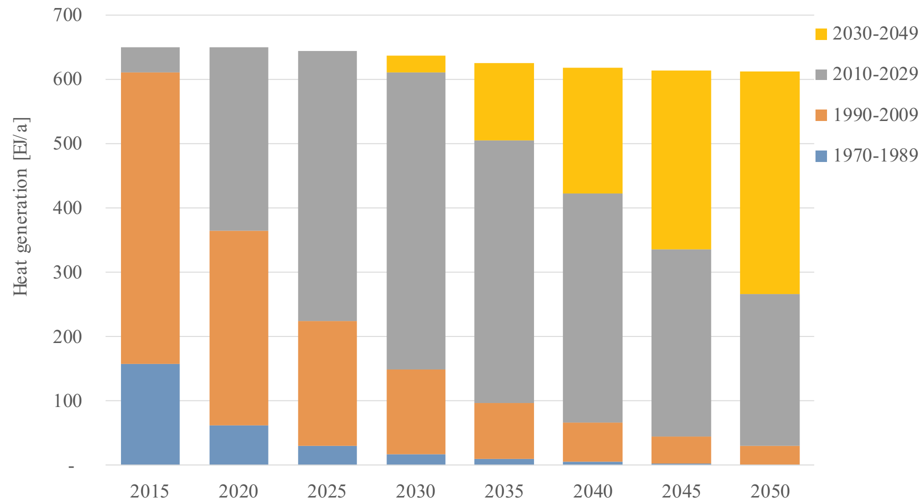

Fig. 10. Example of stock turnover (Germany, current policy scenario, original 5-year-age classes aggregated for presentation).

4.4.2.2. Stock model. The vintage stock model simulates the construction, demolition and exchange of steam generation installations based on their age,[4] steam demand and technology choice. After the initialization of the stock with a given age-structure and technology-distribution, the added and removed capacity is calculated yearly. New installations use the technology distribution calculated via a discrete choice formulation (Equation (6)).

$$\pi_{t,c,y} = \frac{e^{-\lambda U_{t,c,y}}}{\sum_t e^{-\lambda U_{t,c,y}}} \tag{6}$$

With.

$\pi_{t,c,y}$: Choice probability
$U_{t,c,y}$: Utility
λ: Logit parameter
Indices: Technology t, country c, year y

The shares of technologies actually in stock change when new capacity enters the market due to increasing (and thus additional) demand, or when old systems reaching their end of life are replaced. Fig. 10 shows the resulting inertia in the technology stock where units built before 2009 still exist to some extent even in 2050. Feedback from the stock model to the technology choice is included to simulate the observed decision bias that previously used technology trends to replace end-of-life installations without a thorough assessment of the alternatives. This means that a defined share of technologies is replaced by a similar technology without conducting a cost assessment.

A more detailed description can be found in Ref. [6].

4.5. Sub-model space heating and cooling

Space heating accounts for around 10% of industrial final energy demand in Europe [26]. At the same time, its energy saving potentials are expected to be high.

The sub-model for *space heating and cooling* is a compromise between the very low availability of empirical data (hardly anything is known about industrial buildings) and the level of detail needed to capture, e.g. the dynamics and inertia of building and heating system replacement and the long lifetimes involved. The *space heating and cooling* sub-model is separated into two major parts: (1) buildings and (2) space heating and cooling technologies.

The simulation algorithm is based on the following main steps.

1. Calculation of useful heat/cold demand by building class based on a vintage stock model including demolition, new construction and refurbishment of buildings.
2. Calculation of final energy demand based on a vintage stock model for heating systems where the market share of new heating systems is determined by a discrete choice model taking the total cost of ownership of competing technologies into account.

The simulation algorithm for space heating systems is similar to the algorithm described for steam systems and hot water (cf. section 4.4). A detailed description of the space heating sub-model can be found in Ref. [7].

4.6. Sub-model Furnaces

4.6.1. Structure of sub-model

High temperature process heat is often supplied as direct heating, rather than by steam. The applied technologies are very heterogeneous, because the furnaces are specifically designed for the respective industrial process. Examples for important direct-fired furnaces are rotary kilns in clinker burning, blast furnaces in the iron and steel industry and floating (flat) glass furnaces. These furnaces all have very different designs, purposes and process parameters.

However, there is substantial competition among the energy carriers used and switches from one energy carrier to another can be observed in time series of the energy balance. In the *furnaces sub-model,* fuel switching is simulated as price-driven competition among energy carriers for providing process heat above 500 °C. Compared to fuel switching in the *steam systems and hot water sub-model*, we use a more aggregated approach for furnaces that requires fewer technology data, but takes past trends, technology lifetime and energy prices into account.

4.6.2. Simulation algorithm for fuel switching

The backbone of the simulation is formed by a discrete-choice equation that calculates the utility of a given set of energy carriers in a specific sub-sector and country, similar to and partly based on [36,40,53] (for a given year):

$$U_{c,s,i} = \left(\alpha_{c,s,i} * \left(\frac{p_{c,i} - \overline{p_c}}{\bar{p}_c}\right) + \gamma_{c,s,i}\right) \tag{7}$$

[4] Applying a Weibull-distribution, old installations are more likely to fail and be replaced.

With:

$U_{c,s,i}$ = Utility of the energy carrier i in sub-sector s and country c
$\alpha_{c,s,i}$ = Price sensitivity of energy carrier i in sub-sector s and country c
$p_{c,i}$ = Price of energy carrier i in country c
$\bar{p}_c$ = Mean price of all considered energy carriers in country c
$\gamma_{c,s,i}$ = Price-independent constant of energy carrier i in sub-sector s and country c

This equation generates the perceived utility of an energy carrier as a function of its price. However, this utility is influenced by preferences, represented by the parameters α and γ. For example, natural gas is often preferred to coal due to its beneficial properties (stable burning, easier exhaust gas handling, usually available infrastructure), despite the fact that it is much more expensive (based on OECD data, the price for hard coal was around 3 €/GJ, and natural gas was 10 €/GJ in Germany in 2015). These preferences also reflect distinct sub-sectoral characteristics often related to the type of furnaces used, e.g. coke and coal in the iron and steel industry (blast furnaces), natural gas in the glass industry (floating flat glass furnaces), and coal and waste (rotary kilns) in the non-metallic minerals industry. Price-based policies like a CO_2-tax can be included in this approach.

The perceived utility is then translated into a choice probability for a certain energy carrier using the logit formulation of the discrete choice problem (for a given year) [40], similar to the one described in section 4.4.2.

Due to the nature of this formulation, the result is a distribution of choice probabilities for all energy carriers that add up to 1. The energy carrier with the highest utility has the highest choice probability, although this does not scale linearly.

In addition to preferences, the model adds a price-insensitive parameter representing technical limitations to fuel switching. This simulates known technological restrictions. The most prominent example is a minimum requirement of coke in blast furnace operations, as the specialized structure of coke allows mechanical stability and gas flow at the same time, which other energy carriers cannot. Additionally, the model considers the required temperature level of the processes when evaluating different energy carriers (energy replacement ratio according to [5].

It is necessary to simulate inertia in the fuel switch model in order to account for investment cycles, revision periods and other factors that limit the speed of a potential fuel switch. The calculation of market shares is based on [36]:

$$MS_{c,s,i,y} = MS_{c,s,i,y-1} + \delta_{c,s} * (\pi_{c,s,i,y} - MS_{c,s,i,y-1}) \quad (8)$$

With:

$MS_{c,s,i,y}$ = Market share of energy carrier i in year (y) subsector s and country c
$MS_{c,s,i,y-1}$ = Market share of energy carrier i in the last year (y-1) in subsector s and country c
$\delta_{c,s}$ = Diffusion rate of subsector s and country c
$\pi_{c,s,i,y}$ = Choice probability of energy carrier i in subsector s and country c

The equation formally describes a difference between the "optimal" energy carrier share (according to the utility formulation) and its actual market share due to a slowly changing technology stock. A δ of 1 means that there is no difference, effectively cancelling out inertia. Analysing time series suggests values between 0.1 and 0.3, but values as low as 0.04 have been observed in energy balance time series, indicating very long (~30 years) investment cycles. Compared to the calculations in the *sub-model steam and hot water* (4.4), this market share function serves as a simplified stock model.

Fig. 11 validates the sub-model for the period 1992 to 2013 by comparing the historical evolution with the modelled fuel shares. A more detailed description of the approach and systematic assessment of results is presented in a recent publication, in which the authors calculated 0.45 as the coefficient of determination for a time series analysed between 2002 and 2013 [52]. In other words, on average, the model was able to explain 45% of the change in energy use documented in the Eurostat Energy Balance.

5. Model interfaces and add-ons

Depending on the focus of the analysis, it is necessary to extend the sub-models of FORECAST described above. This is currently done using the following add-ons.

1. Carbon capture and storage (CCS)
2. Regional disaggregation and site-specific analyses
3. Hourly electricity demand and demand response
4. Excess heat potentials

5.1. Carbon capture and storage

When carbon capture and storage (CCS) is considered as an emission reduction option, the results from FORECAST are used as input to an external tool. This tool assumes that carbon capture will be deployed if the total cost of sequestration, transport and storage is lower than the total cost of the corresponding CO_2 certificates. The extent to which it is applied in selected industrial processes (ammonia, methanol, ethylene, oxygen steel, lime and clinker production) depends on the achievable return on investment (i.e. a higher cost difference induces a higher diffusion). The assumptions on the carbon capture technology, including the cost development, are taken from Ref. [37]. Major inputs from FORECAST are the total energy demand of the processes and their fuel mix (determining the emission intensity and the treatable amount of CO_2). The detailed consideration of industrial processes in FORECAST allows very specific assumptions concerning carbon capture potentials. Regional matching of carbon sources and sinks is possible with this interface.

5.2. Regional and site-specific analyses

FORECAST's core model calculates on a country level. However, many research questions require analyses with higher spatial resolution. Examples include the location of excess heat potentials, electricity grid requirements as well as distances to CO_2 storage sites.

In order to handle such regional analyses and assessments of structural changes, FORECAST's national level results are disaggregated to a district level (NUTS 3). In this way, the high granularity of the FORECAST results can generate a spatial resolution of energy demand, which enables differentiated conclusions about the individual regions. This regional allocation is made by applying distribution keys. Such distribution keys for the industry sector include the production capacity by process for major processes, and the gross value added by sub-sector for the remaining energy demand. More details can be found in Ref. [18].

5.3. Hourly demand and demand response

FORECAST provides results as annual totals. In order to allow more detailed analyses of load curves and demand response potentials, an interface has been established to the model eLOAD (energy LOad curve ADjustment). ELOAD translates the annual demand evolution into corresponding structural changes in the hourly system load curve (for a detailed description, see Ref. [8,9]. The interface works at the level of individual applications (e.g. a process or a cross-cutting technology).

Some of the processes can be shifted or suspended for several hours to provide flexibility for the electricity system. The optimal deployment

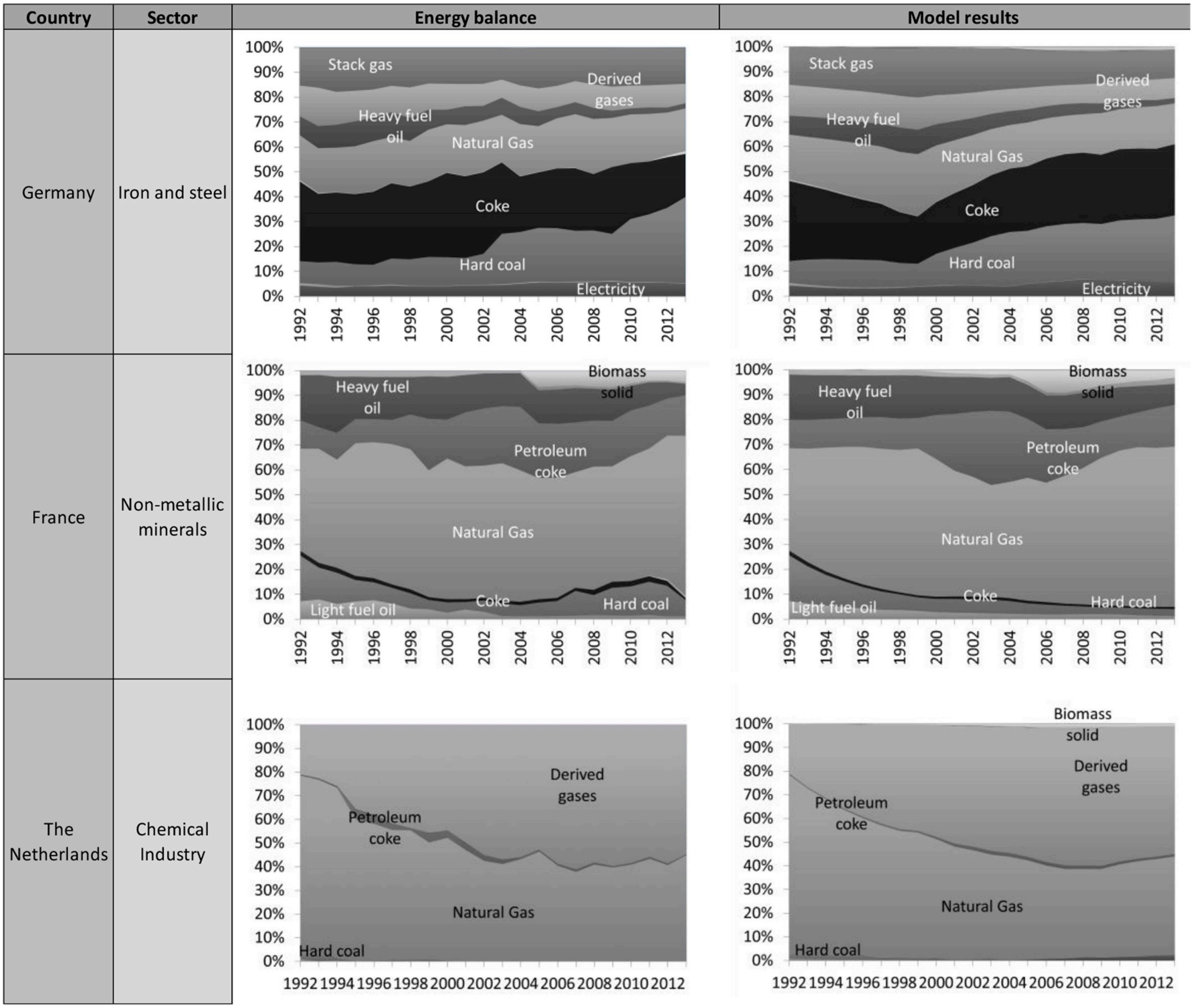

Fig. 11. Comparison of energy balance (Eurostat 2017) and model results for selected sub-sectors and countries for the period from 1992 to 2013 [52].

of these options can be modelled with eLOAD. For example, the electrification of steel production provides additional flexibility: It is assumed that the load of an electric arc furnace can be cut-off for 2 h up to 200 times per year. Another example is electric space heating, which can provide positive and negative flexibility, particularly during the winter. See, for example, [29].

5.4. Excess heat potentials

The calculation of industrial excess heat potentials that could be used in district heating and cooling systems (DHC) is based on a bottom-up estimation of the excess heat available from the main processes of the basic materials industry. To do so, specific excess heat potentials are allocated to individual process/products. Current data includes excess heat sources above 100 °C for about 30 processes. In a second step, specific excess heat potentials are multiplied by physical production to estimate the total excess heat available in a country. Results are available in Ref. [12]. The approach used provides an order of magnitude for the industrial excess heat potentials available in a country. In future research, this could be elaborated by taking into account more products/processes, lower temperature levels, GIS-based matching of excess heat sources with heat demand densities and existing DHC infrastructure, and consideration of today's level of excess heat exploitation.

6. Example case: a mitigation pathway for Germany's industry until 2050

In order to illustrate the applicability of FORECAST, we briefly summarize a recently conducted study supporting the German Federal Ministry for Economic Affairs and Energy with an analysis of a long-term mitigation pathway for the German energy system [50]. The FORECAST model was used to assess the industry sector. The following summary focuses on the main assumptions and results. A more comprehensive summary is available in Ref. [23].

The study examined two scenarios: A reference scenario that simulates the impact of currently implemented policies, economic and technological trends; and a transition scenario that achieves a reduction in GHG emissions for the industry sector of 83% by 2050 (while the entire economy reduces emissions by at least 80%).

Both scenarios assume similar economic framework conditions (regarding gross value added, energy prices and production). The

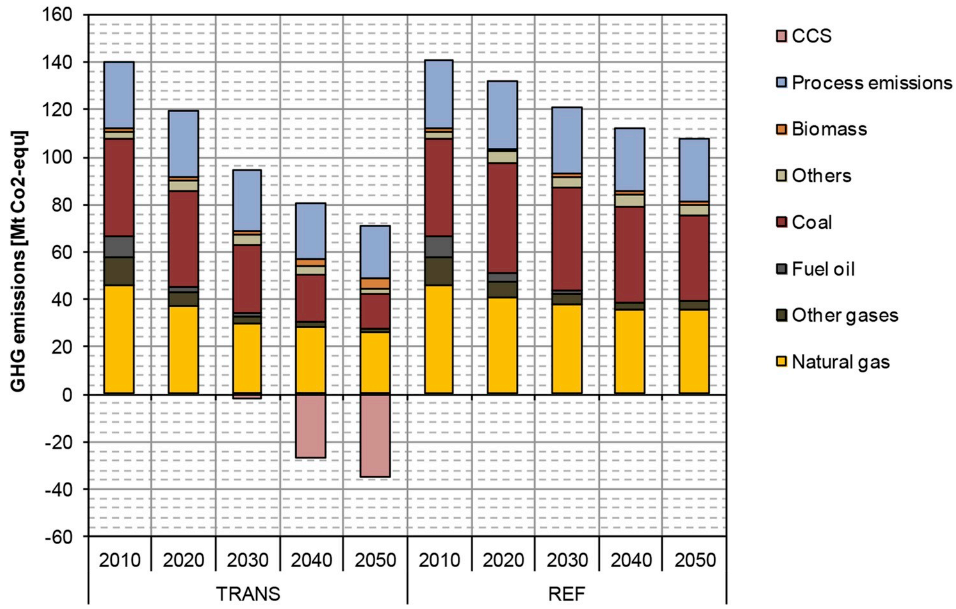

Fig. 12. Illustrative results: Development of GHG emissions from 2010 to 2050 in the transition (TRANS) and reference (REF) scenarios [23].

calculation of the reference scenario shows the advantages of a simulation approach (compared to an optimisation model): It includes individual policy instruments and imperfect markets to mimic realistic investment decisions by companies. Policies included in the reference scenario are energy taxes, the EU emissions trading scheme and minimum energy performance standards. The transition scenario assumes more ambitious and new policies (higher CO_2-price in the EU ETS, CO_2-tax, higher standards, intensive energy management, technology subsidies, etc.). Some key technology assumptions are exogenous including the diffusion of CCS, and the shift towards secondary (recycling) based production (e.g. electric steel replacing oxygen steel) and material efficiency.

Fig. 12 illustrates the resulting GHG emissions for both scenarios. The transition scenario shows a mix of selected mitigation options. It reveals the high importance of energy efficiency, particularly in electric motor systems, innovative process technologies and steam systems. This results in a reduction of electricity demand by about 16% and of fuel demand by about 32% between 2010 and 2050. The use of biomass increases to about 120 TWh in 2050. Coal is phased out in all sectors except the iron and steel industry, which also experiences a drastic shift towards electric steel. Secondary production routes and alternative materials are increasingly employed in the paper, cement, glass and aluminium industries. By 2050, carbon capture and storage mitigates about 35 Mt CO_2 annually from emission-intensive processes (clinker and lime burning, steel, ammonia, ethylene and methanol). Power-to-heat becomes more important after 2040 and reaches about 29 TWh in 2050. Power-to-gas does not play an important role and innovative production processes and products (e.g. the direct reduction of iron using hydrogen from renewables and low-carbon cement types) are not introduced on a large scale. Including these options would achieve even more ambitious reduction targets or replace other mitigation options.

7. Discussion

The modelling methodology presented here is discussed in the light of applying the model to construct transition scenarios to a decarbonised industry sector. Such decarbonisation assessments require a number of key methodological aspects to increase the usefulness of the results for strategic decision-making. These key aspects include:

1. A broad range of mitigation options
2. The transition path
3. Policy levers
4. High level of technology detail
5. Costs

The following section discusses the FORECAST methodology against the background of these five categories and derives possible future improvements.

The presented approach has a broad scope in terms of mitigation options. It considers **energy efficiency** improvements with a very high degree of technology detail, which is one of the model's strengths. Energy efficiency options are included for major processes of the basic materials industry. The non-energy-intensive industries and processes are included via cross-cutting technologies, mainly electric motor systems, and a simple representation of industrial buildings. **Fuel switching** is modelled at a high level of detail in the *sub-models space heating, steam and hot water generation and furnaces*. Thus, the entire industrial heating demand is covered. In the long term, both energy efficiency and fuel switching are also affected by the introduction of new production processes and shifts between processes as defined in the *macro sub-model*. Resource potential cost curves would improve the results, particularly for scarce resources like biomass in extreme scenarios. Similarly, it is difficult to model district heating in detail without considering the regional dimension of heat demand and infrastructure.

By considering the **circular economy and recycling**, the FORECAST model goes beyond many other industry assessments. However, even in FORECAST, their representation could be improved, mainly by ensuring more comprehensive coverage (current focus on metals, paper, and glass). In addition, the representation is (mostly) based on exogenous assumptions. Including diffusion dynamics and limitations as well as the endogenous consideration of material flows would improve the approach.

Energy system analyses, even when focusing on the industry sector, do not typically consider **material efficiency** or the **substitution of products** along the value chain. FORECAST allows the inclusion of exogenous assumptions on material efficiency via changes in the physical production of basic materials products like steel or cement. An advantage of this approach is clearly the large number of products and processes considered via physical production. However, the material efficiency potentials mostly rely on exogenous assumptions. The huge diversity of options available combined with the lack of empirical studies poses a substantial challenge to integrating material efficiency more endogenously in models. A larger number of empirical studies are needed concerning the potentials and dynamics of material efficiency.

CCS is considered after the core model is calculated. In principle, this can be included for all processes considered, however, most assessments include it for the largest CO_2 point sources. While this approach still considers CCS comprehensively, it is a drawback that the modelling is done sequentially and that the current model version cannot consider CCS in competition with other options like new RES-based processes.

With regard to the **transition path**, FORECAST includes important determinants that affect the speed of technical change. The sub-models for stea*m and hot water generation and space heating* include the most detailed technology stock turnover (based on vintage models). For energy efficiency, the diffusion of saving options is modelled endogenously based on diffusion restrictions, prices and policy parameters. A stock turnover model is not appropriate here due to the huge diversity of technologies and measures. The model could be improved in the future by including the diffusion of new production processes and CCS, both of which are driven mainly by exogenous assumptions in the current version.

The consideration of **policies** for energy efficiency and fuel switching has been a major focus of the FORECAST model development. Here, the model can consider energy and CO_2 taxes, technology subsidies, energy efficiency minimum standards as well as OPEX support such as feed-in tariffs for renewables. Other policies like energy management systems or energy audit support to overcome non-financial barriers to energy efficiency are modelled in a more aggregated way by adjusting the parameters for the diffusion of saving options. Policies for recycling and material efficiency need to be considered exogenously.

The high level of **technology detail** is a major strength of the approach compared to other industrial energy models. With more than 60 individual energy-intensive processes and a huge degree of detail in major technology fields like industrial steam generation, FORECAST has sufficient technology granularity for strategy-oriented studies of the entire industry sector. It should be pointed out, however, that sub-sector-specific models (e.g. only aiming at the steel industry) often have an even higher level of technology detail.

Costs are included for all the technologies explicitly considered in the model. These cover OPEX and CAPEX as well as energy expenditures and policy programme costs, like subsidies. Costs are not included so far for material efficiency and recycling options. This is clearly an important priority to improve industry sector modelling in the future in order to obtain more accurate estimates. This will also require more empirical data and case studies for individual sub-sectors or products.

It is essential to **validate** modelling results in order to improve the quality and credibility of model-based assessments. However, it is difficult to validate long-term models, because long time series for historical (input) data are often not available. This problem is amplified by the fact that scenarios aiming at a fundamental change compared to past and current trends cannot be validated by conducting ex-post simulations. Despite this, some parts of the model have been validated. For instance, for the sub-model *fuel switch in furnaces*, an ex-post simulation was compared to existing energy balances for selected countries for the period 1992–2013 (see Fig. 11).

The FORECAST model demonstrates the challenges faced by bottom-up models of the industry sector. These challenges relate to the huge heterogeneity in technologies, companies and energy uses in industry combined with relatively low data availability and a low degree of standardisation. FORECAST addresses these challenges in a modular approach that uses different methods and varies the level of detail in its technology representation. While this approach allows a relatively comprehensive consideration of the entire industry sector and its technologies in one integrated model, it can also be seen as a drawback, because the diverse methods used reduce transparency and make it more difficult to interpret and communicate the results.

The FORECAST model is undergoing continuous development. The methodology described here represents the model in December 2017 after 10 years of development history.

Finally, many research questions related to the energy system transition cannot be answered using models of individual sectors. These questions require a broader perspective of the entire energy system and the economy. For example, recent studies underline sector integration and coupling, which also play a central role for industry. This requires consideration of demand-side flexibility, electricity generation and excess heat supply, among others. For instance, in Ref. [23]; the FORECAST model was combined with an electricity market model to assess the cost and potentials of power-to-heat for industrial steam generation. Such model combinations will play an important role in future decarbonisation assessments.

8. Conclusions

We presented a bottom-up energy demand model to simulate long-term energy perspectives for the industry sector. While the model is suitable for a variety of research questions, the presentation and discussion of the methodology here focused on the model's ability to be used for the development of decarbonisation scenarios.

The FORECAST model can capture a broad range of mitigation options combined with a high level of technological detail. Technology diffusion and stock turnover are considered explicitly to allow insights into transition pathways and speed. The model further aims to integrate different policy levers to improve its applicability as a policy support tool. The model is designed to cover the entire industry sector including major energy-intensive processes at a high level of detail and also the many less energy-intensive sub-sectors and applications.

The model's main strengths relate to its detailed and comprehensive consideration of energy efficiency and fuel switching and a broad range of mitigation options including CCS, material efficiency and recycling. Many industry sector assessments neglect these latter options and this may result in overestimating the cost of reducing emissions.

The model could be improved in the future by including material efficiency and recycling strategies endogenously. These are currently included in the model, but are mostly based on exogenous assumptions. Another improvement concerns the modelling of technology competition, e.g. for new production processes and CCS. These improvements would increase the value of the model's results when assessing industrial energy transition.

Acknowledgements

This paper was compiled with the support of EU funding in the frame of the Horizon 2020 project Reflex (GA-No. 691685). It benefitted greatly from the helpful comments of two anonymous reviewers. We also thank our colleague Gillian Bowman-Köhler for English proof reading. The authors are solely responsible for any remaining mistakes.

Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.esr.2018.09.005.

Annex

Table 4
Overview of industrial processes/products covered in FORECAST.

Non-metallic minerals	Chemicals	Non-ferrous metals	Iron and steel
Container glass	Adipic acid	Aluminium, primary	Sinter
Flat glass	Ammonia	Aluminium, secondary	Blast furnace and converter
Fibre glass	Calcium carbide	Aluminium extruding	Electric arc furnace
Other glass	Carbon black	Aluminium foundries	Rolled steel
Houseware, sanitary ware	Chlorine, diaphragm	Aluminium rolling	Coke oven
Technical, other ceramics	Chlorine, membrane	Copper, primary	Smelting reduction
Tiles, plates, refractories	Chlorine, mercury	Copper, secondary	Direct reduction + EAF
Clinker Calcination-Dry	Ethylene	Copper further treatment	Plasma steelmaking (H2)
Clinker Calcination-Semidry	Methanol	Zinc, primary	Direct reduction (H2)
Clinker Calcination-Wet	Nitric acid	Zinc, secondary	Bath smelting
Preparation of limestone	Oxygen		Direct reduction (Electrolysis)
Gypsum	Polycarbonates		
Cement grinding	Polyethylene		
Lime milling	Polypropylene		
Bricks	Polysulfones		
Lime burning	Soda ash		
Glass electric furnace	TDI		
Less carbon cement (−30%)	Titanium dioxide		
Low carbon cement (−50%)	Methanol (H2)		
Low carbon cement (−70%)	Ammonia (H2)		
Low carbon cement (−95%)	Hydrogen electrolysis		
	Ethylene (methanol based)		
	Ethylene (ethanol based)		
Refineries	**Food drink and tobacco**	**Pulp and paper**	**Others**
Basic refinery	Sugar	Paper	Plastics: Extrusion
Gasoline focused refinery	Dairy	Chemical pulp	Plastics: Injection moulding
Diesel focused refinery	Brewing	Mechanical pulp	Plastics: Blow moulding
Flexible refinery	Meat processing	Recovered fibres	
	Bread & bakery	Paper electric drying	
	Starch		

Table 5
Definition of subsectors in FORECAST according to Eurostat energy balances.

Sub-sector	NACE 2 classification of economic activities
Iron and steel	19.1, 24.1, 24.2, 24.3, 24.51, 24.52
Non-ferrous metals	24,4, 24.53, 24.54
Paper and printing	17, 18
Non-metallic mineral products	23
Chemical industry	20
Food. drink and tobacco	10, 11, 12
Engineering and other metal	25, 26, 27, 28, 29, 30
Refineries	19.2
Other non-classified	All remaining section C

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