Consideration of myopic technological knowledge in long-term energy demand modelling

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Abstract

In order to face the challenge of energy system transformation within the next 20 to 40 years the increase of energy efficiency on the demand side is known to be the most significant driver. Bottom-up based energy-economic models are a tool often applied to analyze energy demand ex ante with a high level of detail. However, because of limited knowledge about the long-term technological progress, the applicability of this approach is restricted for long-term modelling horizons. The objective of this study is to consider technology myopia in long-term energy demand modelling in the residential sector using a newly developed methodological concept that consists of a combination of three well-established approaches utilized in futurology: bottom-up, top-down and patent-based modelling. In contrast to other studies that integrate the advantages of different modelling approaches within one energy model, this concept couples the bottom-up and the top-down model chronologically, including patents as indicators of innovation to consider the myopic technological knowledge. The concept will be applied to the German residential sector in terms of two explorative long-term scenarios up to 2050 to analyze the energy efficiency potentials. Overall, the analysis highlights technological myopia as a key limitation of bottom-up methodology when calculating long-term energy scenarios for the residential sector. For some energy-using appliances (e.g. information and communication end uses) bottom-up based projections are merely possible for short-term horizons (<10 years). To emphasize the added value of the concept, the discussion focuses on methodological issues.

Introduction

In view of climate change, there are political, scientific, economic and social interests in decarbonizing the energy system during the upcoming decades. Increasing energy efficiency on the demand side is known to be the most significant driver of this transformation process (IEA, 2012). One tool for analyzing the impact of energy efficiency on future energy demand is the energy scenario technique based on energy-economic models (Koch et al., 2003; FES, 2002). As the currently discussed transition will take several decades, the time horizon for energy scenarios is often 20 to 40 years (e.g. German Energy Concept (BMWi et al., 2010)). To take into account the diversity of socio-economic and techno-economic drivers, technology-based bottom-up models are applied to describe energy demand with a high level of detail. However, because of limited knowledge about long-term technological progress, the applicability of this approach is restricted for long modelling horizons (Grupp, 1997). This weakness of the bottom-up approach has often been referred to in the literature, but proposals to further develop the method are only discussed to a limited extent (Jebaraj et al., 2006; Suganthi et al., 2012; Vethman et al., 2011).

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The objective of this study is to consider technological myopia in long-term energy demand modelling in the residential sector using a newly developed methodological concept that consists of a combination of three well-established approaches utilized in futurology: bottom-up, top-down and patent-based modelling. In contrast to other studies that integrate the advantages of different modelling approaches within one energy model, this concept is coupling the bottom-up and the top-down model chronologically, including patents as indicators of innovation to measure the technological knowledge stock (Böhringer, 1998; Böhringer, 2006; Koopmans, 2001; Jacobsen, 1998; Rivers et al., 2005). Furthermore, the concept is applied to the German residential sector in terms of two explorative long-term scenarios up to 2050 to analyze the energy efficiency potentials. To emphasize the added value of the concept, the discussion focuses on methodological issues.

Methodological approach

Overview of modelling concept

The methodological concept consists of a combination of three well-established approaches utilized in futurology: bottom-up, top-down and patent-based modelling. The bottom-up model covers final energy demand distinguished by energy-using appliances on an annual basis for the short- to medium-term horizon (Energy Appliance Model; abbr.: EAM). Because detailed techno-economic parameters (such as standby power) are not available in the long run, the top-down model is used for the medium- to long-term horizon, which calculates final energy demand based on energy services (Energy Service Model abbr.: ESM). Thus, in the energy service model, energy demand is abstracted from certain appliances. Losing the information about techno-economic parameters leads to the effect that essential information required e.g. to model the investment decision process or to consider appliance efficiency are no longer available. Thus, the only parameters expected to be available to calculate energy demand in the ESM are the socio-economic parameters (e.g. size of population) and all further parameters that are not technology related (e.g. refurbishment rate). A comparison of the characteristics of both energy demand models is shown in Table 1.

Table 1: Characteristics of energy demand models: EAM vs. ESM

	Energy Appliance Model (EAM)	Energy Service Model (ESM)
Modelling horizon	Short- to medium-term	Medium- to long-term
Energy demand representation	Energy-using appliances	Energy services
Modelling perspective	Bottom-up approach based on simulation	Top-down approach based on regression analysis
Policy consideration	Explicitly per energy-using appliance	Implicitly as techno-economic data is not available
Calibration basis	Empirical data (statistics and studies)	Empirical data and output of EAM

To define the transition between the two energy models, the obsolescence of technological knowledge about certain energy-using appliances needs to be captured. In order to do so, a patent-based model is applied that quantifies technological progress by appliances using an innovation indicator (Knowledge Stock Model, abbr.: KSM). The structural framework of the modelling concept is depicted in Figure 1. This procedure of energy demand modelling and measurement of depreciation rate is conducted for every single energy-using appliance or energy service, respectively. The methodologies applied are discussed in the following sections.

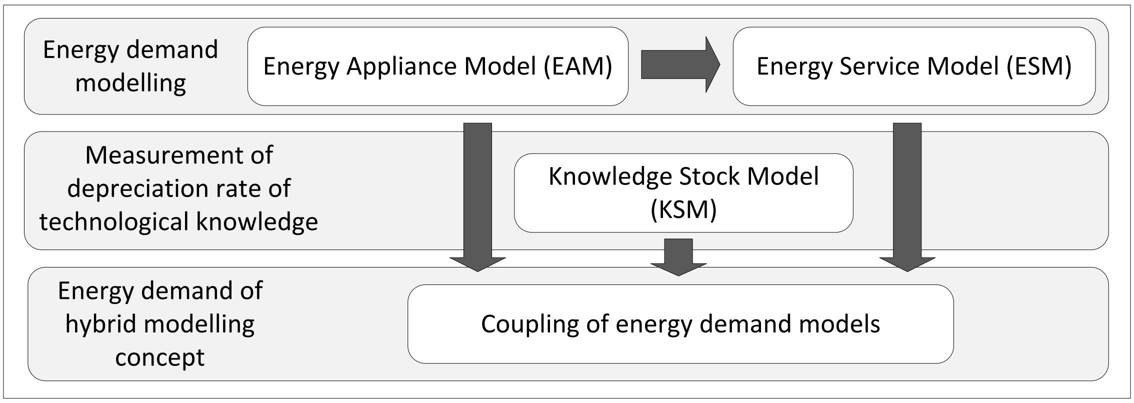


Figure 1: Structural framework of modelling concept

Energy Appliance Model (EAM)

The EAM is constructed as a bottom-up approach, which is based on the simulation method.[3] The simulation method aims to map the system to be modeled as close to reality as possible with regard to its elements, element linkages and characteristics. To calculate energy demand from a bottom-up perspective, the model comprises socio-economic parameters (e.g. size of population) and techno-economic parameters (e.g. operation power) as listed in Table 2. These two types of parameters allow macro-economic drivers to be considered, as well as a detailed representation of the energy appliance stock. As the age distribution of the appliance stock is also captured, the model is designed as a vintage stock model. The technological structure of the model is defined on three hierarchical levels with energy appliances (e.g. televisions) at the highest level of aggregation, which are differentiated by technology (e.g. plasma, LCD) and then divided again into efficiency classes (e.g. A++, A+). The major advantage of this detailed stock representation is that technological change can be modeled under consideration of energy policies, rebound effects as well as barriers on an energy appliance level.

3 To analyze final energy demand based on a bottom-up approach, the model FORECAST-Residential developed at the Fraunhofer ISI is applied. FORECAST-Residential is designed to model the final energy demand on an annual basis for the EU 27+3 (3: Norway, Switzerland, Turkey) by country up to 2050. Due to its high degree of technological detail, FORECAST is used to examine both energy and climate policy instruments (Matthes et al., 2013) and for scenario analyses at a national (Elsland et al., 2013c), international (Elsland et al., 2013d) and European level (ESA2, 2013).

Table 2: Techno-economic and socio-economic parameters of the EAM (selected)

Techno-economic parameters	Socio-economic parameters
Ownership rate per energy-using appliances	Size of population
Market share of technologies / efficiency classes	Number of dwellings / buildings
Operation / standby power	Dwelling surface
Operation / standby hours	Litres of hot water usage
Lifetime (reinvestment cycle)	Gross domestic product (GDP)
Investment, maintenance and energy costs	Energy carrier prices for end consumers

The ownership rate per dwelling of household energy appliances is determined by the Bass function, which is shaped as a sigmoid growth curve (Bass, 1969). The Bass function is based on the empirical evidence that word-of-mouth recommendation is the key driver of innovation diffusion (Albers, 2004). As decision-makers in private households differ with regard to their individual utility due to different lifestyles, available information and other characteristics, the type of appliance chosen can vary greatly. To consider heterogeneous user behavior, the adoption of new appliances is modeled based on a multinomial logit approach (MNLM) (Tutz, 2000). In the EAM, the MNLM captures market heterogeneity on a macroeconomic level for a 'representative individual' by describing the diffusion process of substitution alternatives by market shares. The key descriptive factor used to define the individual utility of a decision-maker is the Total Cost of Ownership (TCO): the TCO comprises the required initial investment as well as any costs for energy and maintenance. Calculating the TCO is done using a dynamic net present value calculation, which allows different investment alternatives to be compared in monetary terms (Götze, 2006).

Energy Service Model (ESM)

As techno-economic parameters are often not known for long modelling horizons (see left column of Table 2), the calculation of medium- to long-term energy demand is based on a top-down approach (Gordon, 2005; Diekmann et al., 1999). In this top-down model, calculating energy demand is abstracted from certain appliances and represented by energy services. An energy service can be defined as an individual's need, which can be covered by useful energy and other production factors (VDI, 2003). As energy services are a more abstract manner for describing electricity demand, the amount of services in the ESM is diminished to 12 in comparison to 32 energy-using appliances in the EAM (Table 3).

Table 3: Assignment of energy-using appliances to energy services

Energy service	Energy-using appliance
Food preservation	Freezers, refrigerators
Laundry	Washing machines, dryers, irons
Dish cleaning	Dishwashers
Food preparation	Stoves, microwaves, exhaust hoods, coffee-machines, toasters
Information & communication (end-uses)	Televisions, Computer screens, laptops, desktop PCs
Information & communication (infrastructure)	Set-top boxes, modems & routers
Miscellaneous energy services	Small appliances (e.g. vacuum cleaners, hair dryers)
Lighting	Lamps
Room conditioning (cooling & ventilation)	Air-conditionings, ventilations
Room conditioning (heating)	Boilers, heat pumps, night-storage heating, radiators, solar systems
Water warming (heating)	Instantaneous water heaters, boilers, heat pumps, solar systems
Heating (infrastructure)	Circulating pumps

Nevertheless, to ensure consistency between the two energy demand models from a scenario perspective, the impact of policy measures, rebound effects, changing energy carrier prices and other socio-economic parameters on energy demand need to be considered in the ESM as well (Kavgic, 2010). The selected methodology chosen that is able to provide this flexible scenario design is econometric regression analysis (Tutz, 2000). The parameterization of the regression function is derived from elasticities of EAM results. Thus, in spite the fact that detailed techno-economic data is no longer available for long-term modelling horizons, the impact of parameters influencing technological change like energy carrier price development remains. The data to parameterize the top-down model consists of two datasets, output data of the bottom-up model and empirical data. The time horizon of the bottom-up model's output data is determined by the pace of technological progress of each energy-using appliance (see KSM). Taking empirical data into account extends the data used to parameterize the top-down model, which leads to more reliable regression coefficients.

Transition Stock Model (KSM)

The knowledge stock per energy-using appliance calculated by the KSM is the key driver to derive a time span in which the calculation of energy demand shifts from the bottom-up to the top-down approach (Figure 2).[4] This knowledge stock depends on the innovation dynamics and the resulting pace of technological progress of each energy-using appliance. Thus, the heterogeneity of energy-

[4] The coupling of EAM with a patent analysis has already been discussed in (Elsland et al., 2013a; Elsland et al., 2013b).

using appliances leads to the effect that the transition period between the energy demand models differs depending on the innovative characteristics by appliance. The KSM is based on patent applications due to the facts that statistically significant basic population of patent data is available in publicly accessible databases (e.g. at the German Patent and Trademark Office), patent documents are standardized in the International Patent Classification (IPC) and patents do have a high market proximity (DPMA, 2006). Patents certify the protected rights of inventions to give inventors the exclusive right to economically exploit the patented invention for a defined duration (Gerpott, 2005; Rammer, 2002).

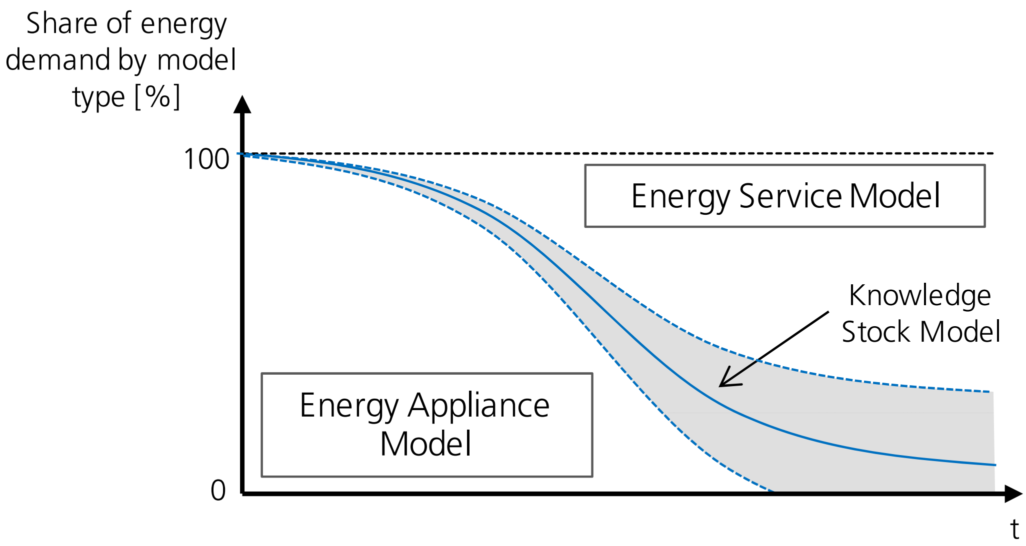


Figure 2: Schematic representation of model interaction under consideration of a differing pace of technological progress of each energy-using appliance

When using patent indicators to quantify technology progress, a concordance has to be defined between energy appliances and patent classes. Therefore, appliances are broken down into functional components based on technical documents to derive IPC patent classes. The indicator applied for quantifying technological progress is the technological cycle time indicator (TCT indicator) (Narin et al., 1993; Kayal, 1997; Daim et al., 2008; Jochem et al., 2009). The TCT indicator is based on the fact that new patent documents use backward citations to refer to existing patents on which the new patent is based. This yields a direct correlation between the age of the cited patents and the pace of technological progress: the younger the cited patents, the faster the technological progress and vice versa (Fabrizio, 2009). Within the KSM approach, the TCT indicator is defined as the average age of the citations made by a new patent to existing patents (Park et al., 2006). Thus, the age of a citation is the time span between the priority date[5] of the cited patent and the priority date of the citing patent.

As the TCT indicator captures the cumulative characteristics of technological progress, the technological cycle time permits conclusions about the magnitude of technological myopia (Park et al., 2006). But, the TCT indicator only represents the expected value for the period of time between two interrelated and successive developments of one technology. Since a technology field comprises large numbers of patents, there is further development taking place significantly before or after this time

[5] The priority date is when the patent application was first submitted to a patent office.

span. This implies a continuous drop in the ability to explain the future state of technology development (Narin et al., 1993). Analyzing empirical patent data of the German Patent and Trademark Office (DPMA) within the period 1990-2010 indicates that backward citations are developing exponentially (DPMA, 2012). Due to this empirical evidence, the obsolescence of technological knowledge is modeled by exponential depreciation rate (Machlup, 1962).

Coupling the energy demand models

When coupling the energy demand models, the appliance-specific depreciation rates serve as a weighting factor of energy demand calculated by the bottom-up (EAM) and top-down (ESM) approach. The technological knowledge starts with the value of 100% in the presence, assuming complete knowledge about the current technological state-of-the-art for each energy-using appliance. Consequently, energy demand is calculated completely by the EAM in the base year of the projection. With a receding time horizon, the obsolescence of technological knowledge increases and therefore more and more energy demand in the hybrid modelling concept is explained by the ESM. The annual energy demand of the hybrid modelling concept comprises two parts: the energy demand of the EAM weighted with the technological knowledge of each appliance and the energy demand of the ESM weighted with the complement of the technological knowledge stock per energy service.

Case study: Scenario analysis of efficiency potentials in the German residential sector until 2050

Scenario definition

The hybrid modelling concept is applied in two explorative long-term scenarios for the German residential sector until 2050 to analyze the energy efficiency potentials: a reference scenario (REF scenario) and a high-policy-intensity scenario (HPI scenario). The scenarios focus on electrical driven appliances. The scenarios differ with regard to the ambitiousness of energy policy regulations. In both scenarios it is assumed that the energy policy laws and directives which have already been passed, such as for example the Eco-design or Labelling directives, are successfully implemented. While the reference scenario assumes moderate amendments to these regulations in the future, the high-policy-intensity scenario reckons a much more ambitious design of these energy policy measures. It is assumed that efficient and innovative energy-using appliances are introduced into the market with a higher frequency in the high-policy-intensity scenario due to its policy framework.

Results

At first, the key findings of the REF scenario are discussed. The framework conditions defined in the REF scenario lead to a decrease of electricity demand from 139.5 TWh in 2008 to 137.1 TWh by 2050 (see Figure 3, left side). Analysing the results of the EAM on an energy-using appliance level shows that except for heat pumps stock increase more or less compensates efficiency improvements. Analysing the shift from EAM to ESM energy demand calculation highlights that beyond 2034 more than 50% of the electricity demand is described by energy services, whereas the percental share of overall electricity demand calculated by the ESM increases up to 84.3% by 2050 (average annual decrease of EAM electricity demand between 2008-2050 is -2.0%). This means that just for 15.7% technological knowledge is sufficient to calculate electricity demand based on techno-economic parameters (EAM).

Especially for energy-using appliances like ICT with short reinvestment cycles (lifetime < 10 years) and a fast pace of technological progress (TCT < 10 years) the consideration of technological myopia plays a crucial role. Already in 2018 only 50% of electricity demand is calculated based on the EAM and by 2024 the last known ICT-appliances are eliminated from the market. This is based on the fact that new ICT-appliances diffusing into the market have a very low share of technological knowledge. On the other hand energy-using appliances with long reinvestment cycles and a slow pace of technological progress such as direct heating are still calculated based on techno-economic input parameters by 34% in 2050. Accordingly, depending on the appliance characteristics the share of EAM and ESM fluctuate strongly, which emphasizes the strengths of the integrated modelling concept.

In contrast, in the HPI scenario electricity demand decreased down to a level of 100.2 TWh by 2050 (see Figure 3, right side). This is a difference of 36.9 TWh in comparison to the REF scenario. In the HPI scenario the share of 50% of the ESM based energy demand calculation is already reached in 2030. The percentual share of the overall electricity demand calculated by the EAM in 2050 accounts for 1.3 % (average annual decrease of EAM calculated share of electricity demand between 2008-2050 is -2.2%). Thus, only a small share of heating system electricity demand (1.3 TWh) is still calculated based on the bottom-up approach in 2050.

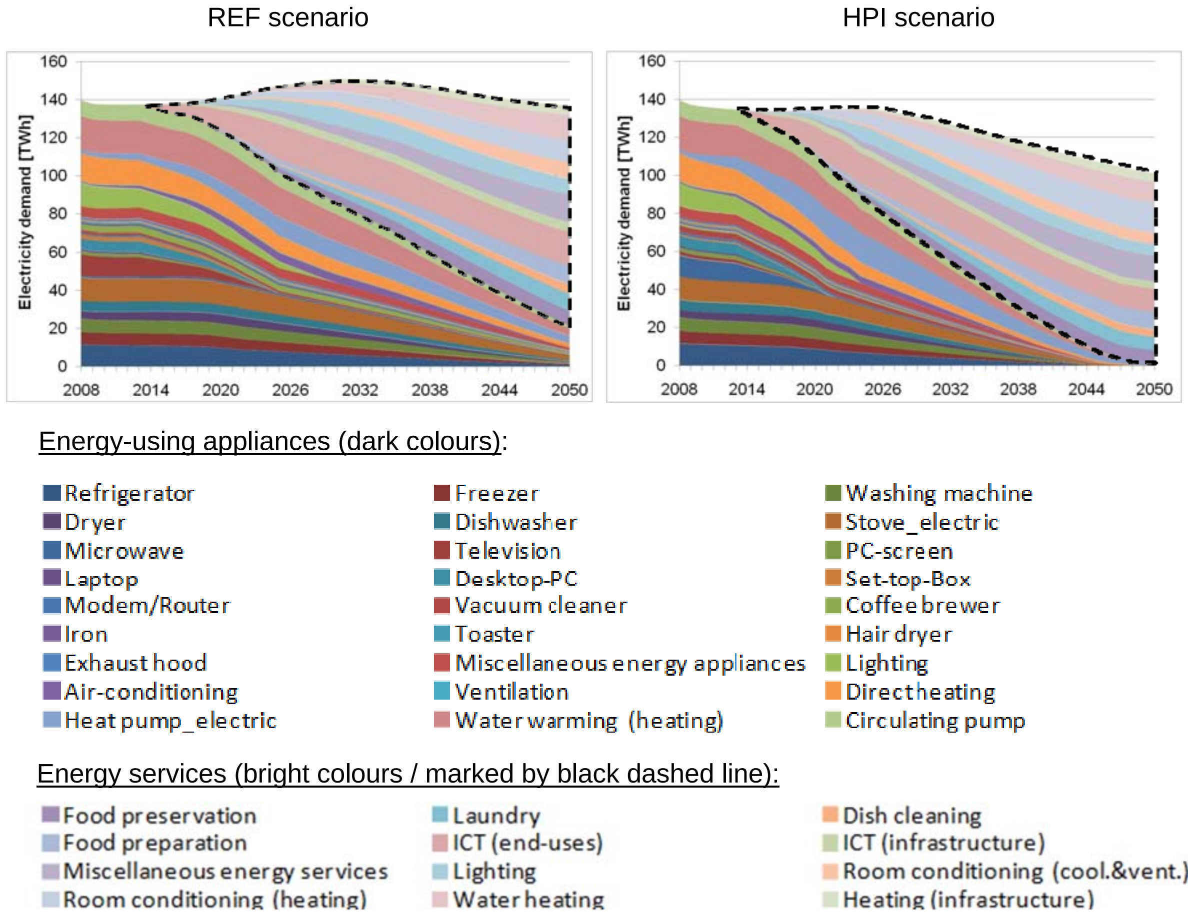
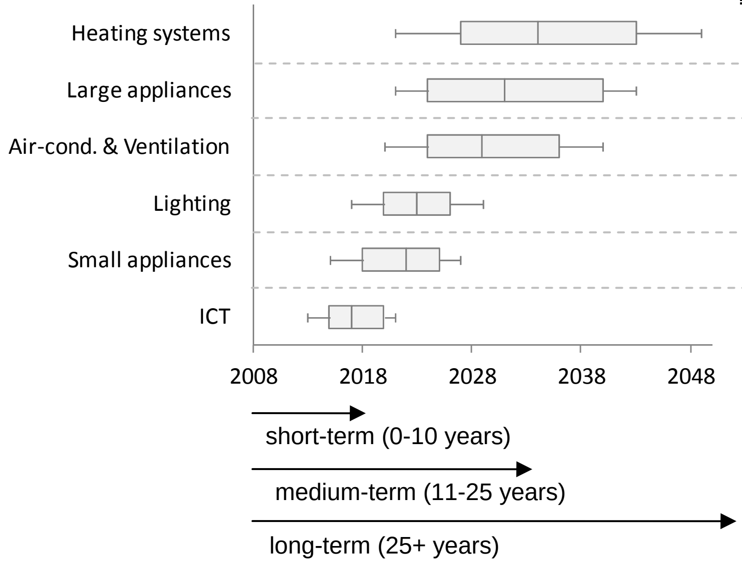


Figure 3: Electricity demand of the hybrid modelling concept for the period 2008-2050: REF scenario (left side) and HPI scenario (right side)

A more detailed analysis on an energy-using appliance level emphasises that the suitability of modelling energy demand based on a bottom-up approach depends largely on the type of appliance. In Figure 4 clusters of energy-using appliances are listed and sorted by their share of bottom-up modelled time horizon. Besides various TCTs energy-using appliance heterogeneity is based on different reinvestment cycles, market entrance and elimination as well as adoption behaviour. The arrows labelled with the time horizons beneath the box plots graph give an indication when it comes to the capability of time horizons that could be modelled on a bottom-up basis. To emphasize the impact of technological myopia on residential electricity demand, information concerning the share of electricity demand in base year and the trend of electricity demand development is further added in Figure 4. Consequently, the significance of technological myopia of each energy-using appliance regarding long-term bottom-up modelling is enhanced or weakened by these two categories.



	Share of electricity demand in 2008	Trend of electricity demand development
Heating systems	30.3%	decreasing
Large appliances	33.6%	decreasing
Air-cond. & Ventilation	0.7%	increasing
Lighting	8.8%	decreasing
Small appliances	10.5%	increasing
ICT	16.1%	increasing

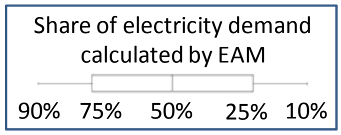


Figure 4: Scattering of bottom-up calculated share of energy demand by energy-using appliance clusters complemented by their share of electricity demand in the base year and trend of electricity demand development for the period 2008-2050

Conclusions

Overall, the analysis highlights that technological myopia is a key limitation of bottom-up methodology when calculating long-term energy scenarios. The discussion about the chronological coupling of different types of energy demand models in combination with patent indicators illustrates that the modelling concept developed enables a more transparent analysis of energy scenarios than conventional bottom-up studies. The integrative concept essentially provides two general advantages:

(I) There is no fixed year defined at which energy demand could no longer be calculated on the basis of a bottom-up approach, rather the transition from EAM to ESM is designed smoothly. Thus, this approach is capable capturing the evolutionary process of technological change.

(II) Although it is assumed that techno-economic parameters are no longer available for the medium- to long-term horizon, scenario compatibility is provided as their influence on energy demand is implicitly considered by calibrating the ESM based on EAM elasticities. Thus, even if just the set of socio-economic parameters is identical in both energy demand models, linear and linearized regressions of ESM are capable of implicitly capturing the impact of techno-economic parameters on the results (e.g. energy policy regulations).

Besides these general advantages there are three model specific advantages:

(I) all strengths of bottom-up modelling are retained for the short- to medium term projection horizon,

(II) by including an innovation indicator an energy-using appliance specific time horizon can be defined that determines the point in time, when energy demand can no longer be calculated via techno-economic parameters,

(III) for the medium- to long-term projection horizon energy demand is abstracted from certain energy-using appliances and represented by energy services, whereas energy demand is still calculated on a high level of granularity due to the decomposition approach.

Although the gradual transition from EAM to ESM is calculated endogenously from patent time series, it has to be emphasized that market entrance of innovations is determined exogenously in vintage stock models. Up to the present day innovation theory does not provide any approach to derive this point in time, especially not for long-term horizons until 2050. As the determination of market entrance has a significant impact on energy scenario results, this has to be taken into account when interpreting the degree of technological myopia. According to conventional bottom-up models the point in time when innovations enter the market is an exogenous input parameter in the modelling concept developed as well. The estimation is based on empirical market data and energy policies that regulate the placing of efficient energy-using appliances on the market. This estimation of market entrance is a limitation of long-term scenarios due to epistemological reasons and not attributable to the methodological elaboration of the concept. A further parameter that cannot be defined precisely from a scientific point of view is the maximum level of an appliance’s energy efficiency. For this purpose, potential estimations of current studies about best not yet available technologies are taken as an approximate value for the long-term maximum level of an appliance’s energy efficiency.

Furthermore, it can be concluded that the developed concept only models incremental changes of technological progress, whereas radical changes like wild cards or black swan technologies that are per definition not foreseeable in the long-term are not considered (Hiltunen, 2006; Mendonca, et al., 2004). Moreover, the concept developed focuses on existing energy services. New types of energy services that provide a new utility were not considered in the conceptual development. This issue is also related to an epistemological problem that cannot be solved ex ante, as the prospective technological development regarding new energy services is per definition unknowable. In terms of applicability, the analysis showed that the methodological design of the concept for the consideration of myopic technological knowledge in long-term energy demand modelling is not restricted to the German residential sector. This concept can also be transferred to the residential sector of other countries or to other sectors.

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