A function-based approach to stock modelling applied to compressed air systems

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Abstract

Achieving current EU energy targets will require substantial improvements in energy efficiency across a broad range of industrial end-uses. While compressed air systems are important contributors to overall industrial electricity demand, substantial energy-efficiency potentials have been identified in the past. Various policy measures can be designed to exploit these saving potentials. Yet when efficiency improvements depend on replacing existing equipment, the impact of policy measures depends not only on their design, but also on the structure of the addressed end-uses. Stock models may serve to provide quantitative data regarding the impact of different policy measures on energy demand. But data availability is often a limiting factor for using stock models, as information about production, age, operating conditions and thus the structure of the energy demand of specific end-uses is often only available to a limited extent.

In this paper, we therefore suggest a "function-based" bottom-up stock model approach. The basic idea of this modelling approach is to use both proxy functions to fit available data and to use expert estimations on functional parameters where little data is available. To a certain extent, this is common practice for some variables (e.g. for lifetimes), but we suggest to extend this idea to other energy-relevant characteristics. The advantage of this modelling approach is to provide detailed results with only a limited number of assumptions that can be stated in a very transparent manner. It thus can also improve the understanding of energy demand and help to evaluate the impact of policy measures. We apply this approach to a case study on compressed air systems in the EU in order to illustrate its benefits.

Introduction

Improving energy efficiency is considered one of the key pillars in the development towards a more sustainable global energy system (OECD/IEA 2010). While there are substantial energy-saving potentials in the industrial sector in the European Union (Eichhammer et al. 2009; EC 2009), these potentials are often unexploited despite their economic and environmental benefits. This phenomenon is attributed to various barriers to energy efficiency and has been termed the energy-efficiency gap (Hirst and Brown 1990; Jaffe and Stavins 1994; Sorrell et al. 2011). European policy-making recognises the opportunities related to energy-efficiency improvements by promoting different energy-efficiency policies. In its strategy for 2020, the European Commission sees the 20-20-20 goals as one of five headline targets for Europe, including a 20 % increase in energy efficiency (EC 2010). Next to this general goal-setting, specific action concerning the industrial sector has been taken among others by introducing the Ecodesign framework (Directives 2005/32/EC, 2009/125/EC), which results in regulations on important energy consumers such as electric motors, fans or circulators[1]. Another important consumer of electrical energy in industry are compressed air

1. See http://www.eup-network.de/product-groups/overview-ecodesign/ for an overview.

systems (CAS). In 2001, they were responsible for about 10 % of European industrial electricity consumption (Radgen and Blaustein 2001). Considerable cost-effective potentials to improve energy efficiency in CAS have been identified (UNIDO 2010; EC 2009; Radgen and Blaustein 2001), which amount to more than 30 % of the electricity consumption of CAS (Radgen and Blaustein 2001).

With regard to addressing such or similar energy-saving potentials, policy-makers can consider various policy measures to actually meet overall efficiency goals. However, efficiency improvements related to technological replacements are only gradually diffusing into industrial energy systems, as the penetration of these improvements is restricted by technological replacement cycles. As a means of explicitly analysing the penetration rate of more efficient technologies, and thus the impact of related policy measures, quantitative stock modelling is required. Data availability is often a limiting factor in setting up stock models. Information on the installed number of units, their age structure, their operating hours or installed power is often only available to a very limited extent. Thus stock models addressing specific industrial applications are often rather crude and only allow reliable quantitative computations of the penetration of efficiency improvements to a limited extent. Furthermore, many stock models only possess a limited degree of transparency since large amounts of underlying data are handled, for example, only in unpublished data files. In such cases, the methodology may be mentioned, but the computations can hardly be repeated by third persons. Yet transparent stock models and methodologies can help to foster a better understanding of the effectiveness and actual savings related to different technological improvements triggered by policy measures.

In this paper, we therefore propose a function-based stock model approach which allows a) using either statistical distribution functions instead of disaggregated or highly aggregated raw data or b) using simple functional descriptions where little information is available. Independently of the method used, this approach has the advantage that it always states methods and results in a clear manner. To present this approach, we proceed as follows: we first provide initial background information on CAS, as we will analyse this end-use to illustrate the suggested concept. We will then provide an overview of different types of stock modelling approaches. Against this background, we will detail the central ideas of our stock modelling approach. This is followed by a case study on industrial air compressors to illustrate our approach, before we discuss the related advantages and challenges and then draw some general conclusions.

Compressed air systems in industry

Next to natural gas, steam and electricity, compressed air is considered the fourth utility in industrial companies (Yuan et al. 2006). It is used for a large variety of different purposes, e.g. for pneumatic actuators, compressed air tools, as process air, for vacuum applications or for control purposes. With some exceptions for special applications, stationary industrial air compressors are usually powered by electric motors. Typical compressor types in industrial applications are helical-screw compressors, piston compressors and centrifugal compressors (Bloch 2006). While all components used in a CAS determine its overall energy demand, the compressor is the most relevant consumer of electrical energy in a CAS. Thus it can be used as a good proxy to analyse the energy demand of CAS.

With regard to the energy demand structure of industrial CAS, comparatively little information is available and the structure of existing data is very heterogeneous. A rather detailed analysis for the European Union based on a simple stock model was carried out by Radgen and Blaustein (2001) who provide information on the energy demand and stock of air compressors between 10 and 300 kW for the European Union and several larger countries. Larger and smaller installations are excluded, the former usually being integrated in well-maintained systems and the latter being of little relevance for aggregate energy demand. The results of this study indicate an overall stock of about 320,000 compressors in the considered segment for the EU (in the boundaries of 2001), corresponding to an aggregate electricity demand of 80 TWh or 10 % of overall industrial electricity demand. Other publications provide further indications on the structure of CAS in various countries: in a general assessment of energy demand by end-uses in Germany, Rohde (2010) provides an overview of energy demand for CAS in various industrial branches. For the United States, an assessment of compressed air usage in 222 companies provides information on the installed compressor capacity in these companies, disaggregated by industrial branch (US DOE 2001). A similarly structured study was carried out for Serbia with 52 companies (Šešlija 2011). For New Zealand, Neale and Kamp (2009) provide an estimated energy demand of CAS by different segments of installed compressor capacity and attribute a number of sites to each category. And finally, an analysis for Switzerland was conducted by Gloor (2000) who provides information on the number of sites with different installed capacities also differentiated by branches.

While each of the cited studies provides some information on the structure of CAS energy demand, the aggregation levels and scope of the different studies are quite heterogeneous, thus making it difficult to compare the different studies, reuse the data and to provide overarching conclusions. Yet these studies suggested that actually very little knowledge appears to be available on the actual structure of energy demand of air compressors in industry.

Stock models

Stock models can serve as a means to describe and analyse the structure of energy demand. They are mathematical descriptions of how objects or sales build a stock of objects or products over time. As a general rule of stock modelling, the size of a stock of objects within a system is characterised by four parameters: the number of objects entering and leaving the system and the number of generated and destroyed objects within the system. The latter two parameters are not relevant here, thus the basic ingredients to model the stock of air compressors are a combination of information on production (entering objects) and product lifetimes (leaving objects). In stock models, time can be represented either discretely or continuously. In the case of discrete time, each step in time represents one year or other instances of time separated by constant differences. A simple and easy way to use a stock model is given by (see, e.g., Bucher et al. 2011):

$$M(t) = \sum_{u \le t} N(u) \cdot L(t-u)$$

Here, $M(t)$ is the total stock of objects in year t, $N(u)$ denotes the sales in year u, $t - u = a$ represents the age of the objects sold in the year t, and $L(a) = 1 - F(a)$ is a survival function describing the relative evolution of remaining objects. The formula simply expresses the total number of objects in stock as those that still survive from earlier years u with their respective probability of survival in the year t. The age-dependent cumulative scrapping probability $F(a) = \int_{0<x<a} f(x)\mathrm{d}x$ is a function of the age-dependent scrapping rate $f(x)$. The latter function could for example be a Weibull or simple exponential function. The survival probability $L(a)$ could also be a simple stepwise function, such that all products younger than a lifetime T remain in stock and all older items are directly removed from stock.

A second kind of stock model, widely used in modelling biological populations, is based on the Leslie matrix (see Cushing (1998) for an introduction). Let us denote the number of objects of (discrete) age a in year t by a time-dependent vector $\mathbf{z}(t)$ having components $z(t;a)$ such that the total stock in year t is given by:

$$M(t) = \sum_{a>0} z(t;a)$$

After one time step, the age distribution is altered because new objects enter with age 0, the existing items turn one year older and objects at age a are removed from stock with an age-dependent probability $L(a)$. The latter means that only some objects of age a survive until the next year. Taking this together, the time evolution for objects at age a reads:

$$z(t+1;a+1) = L(a) \cdot z(t;a) \text{ for } a > 0 \text{, and}$$

$$z(t+1;a+1) = N(t)$$

The time evolution can also be written in vector and matrix notation:

$$\boldsymbol{z}(t+1) = \boldsymbol{L} \cdot \boldsymbol{z}(t)$$

One difference between the two approaches[2] is that the former needs the sales of many earlier years as input whereas the latter can be used with data from a starting year, say the present year, but instead requires the present age distribution of the stock under consideration. These stock models can be directly extended to more degrees of freedom, e.g. to different types of compressors or different power classes. Both models have in common a need for high quality data and are well-known and widely used in different contexts (Bucher et al. 2011, Cushing 1998 and references therein). Already mentioned were the ecological applications in mathematical biology that are applied to model single populations of fish, birds, bacteria and many other biological species (Cushing 1998). Quite often the interaction between different species plays an important role, such as predator-prey or symbiosis relations. These can all be described by the stock models introduced above and strict mathematical results have been obtained, e.g. on the extinction of individual species. With regard to applications in energy research, stock models can for example provide information on the number, efficiency and age structure of appliances such as refrigerators, buildings and other energy-related equipment (see e.g. Bucher et al. 2011). An essential step in such energy-related applications of stock models is, of course, to translate stock information into information on energy consumption, thus adding additional data to the stock information.

Both types of stock models require good and comprehensive input data. This includes data on sales of many earlier years or the current age distribution and age-dependent scrapping rates. This data is required for each product or end-use. While data is sometimes available, authors often do not provide the input data explicitly or only at very aggregated levels. For example, the large study of Radgen and Blaustein (2001) provides only two aggregated power classes (10–110 kW, 110–300 kW) across all types of compressors. This has two disadvantages: first, only very little of the information contained in the collected large dataset is used and much is simply lost by direct aggregation to a few classes of products only. Second, presenting data at an aggregated level reduces the transparency of a study and makes it difficult to reuse the data. Of course, not all individual data points collected in a study can be made available in a print, but a reasonable number of the input data could be shown and presented in a more reproducible way (see our proposal in the next section). In other cases, only very little information is actually known with certainty. Nevertheless, experts can often provide a direction or general trend as to what the actual situation is likely to look like. Even if such information does not have the same quality and reliability as detailed quantitative data, it can at least provide some basic insights into the general structure of a situation.

We thus conclude from the present section that good and reliable stock models are mathematically available. Yet with regard to stock modelling in energy research, problems arise from a lack of data, from the quality of available data, from the way data is used and from the transparency of the data usage. With many projects collecting data in Europe and other regions of the world, e.g. on motor-driven systems such as CAS, resolving the former problems could simply be a matter of time. In contrast, the issue of making good use of the data and presenting it transparently to other researchers needs efforts from the research community. The suggested approach in the next section is aimed at obtaining detailed, transparent and reliable stock models for energy research in the future.

Proposal for a function-based approach

To tackle the discussed issues of data handling and to provide an opportunity to include estimates in stock modelling, we propose using simple mathematical functions to provide input data for stock models. That is, we suggest using the existing mathematical framework of stock modelling presented above, but extend it either a) by introducing statistical distribution functions instead of disaggregated or highly aggregated raw data or b) or by using simple functional descriptions where little information is available.

Let us consider the first idea in more detail: Currently, stock models rely on classes of products or technologies based on aggregated raw data. We argue that this raw data could be used

2. A third class of models uses time as continuous quantity. Then the latter approach can be used as well, but leads to a partial differential equation (see again Cushing (1998) for an introduction). We will not pursue the continuous time version further here.

more effectively and more transparently if statistical distribution functions were used to fit this data. Mathematically, we suggest replacing average values for some property P or the few class values P_x by a continuous distribution function $P(x)$. This takes into account that users or adopters of technologies often differ considerably in their characteristics or that even the same technologies or end-use can possess very different characteristics, e.g. different sizes. As a means to describe detailed raw data, we therefore suggest matching the shape of input data by using probability density functions (pdf) $f(x)$ and cumulative distribution function (cdf) $F(x)$, and using these functions for computations. The cumulative density function $F(x)$ for probabilities with non-negative domain is defined as:

$$F(x) = \int_0^x f(r)\mathrm{d}r$$

An illustration of this idea with regard to the power of air compressors is provided in Figure 1. The most detailed, publicly available information on the structure of air compressor sales by compressor size appears to be provided by Gloor (2000) in Switzerland. This data provides an overview of sales information of seven larger manufacturers in 1998, differentiated by compressor capacity and compressor types. The overall sales included in the sample amount to some 2,500 units, depicted in Figure 1 by dots. The available sample data is already aggregated and includes compressors in a power range from 1.5 kW to 250 kW, segmented by 21 different classes of compressor size. The size of the segments increases with compressor size and the data suggests that the overall sales are dominated by small compressors.

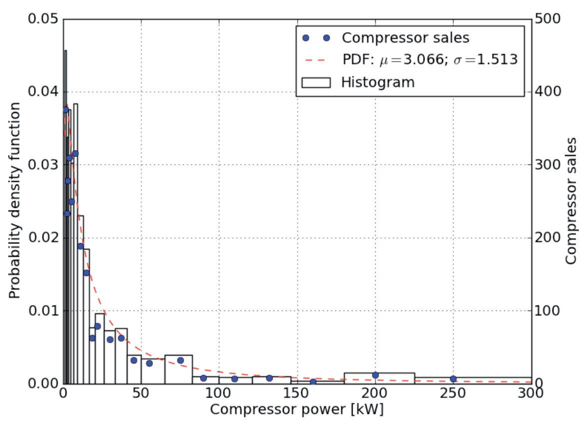
As a mean to represent this data, we fit the data by a probability density function. For this purpose, we use the pdf of a log-normal distribution for the compressor power for several reasons: first of all, it shows acceptable agreement with the observed data. Secondly, it is well known that the empirical distribution of firm sizes is approximately log-normal (Sornette 2000). Assuming that large compressor powers are needed only in large companies, the distribution of compressor power should roughly be similar to the distribution of company size. Though we are aware of the fact that companies differ largely in their energy consumption and need of compressed air, irrespective of their size, we still use the fact that energy consumption per capita over different industrial segments is at least a peaked distribution (see Plötz and Fleiter (2012) for a more detailed discussion of this issue). Furthermore, the log-normal distribution has a rather natural interpretation in the present case: many factors contribute to the installation of a compressor of certain power in a company. Such factors include, for example, the likelihood of belonging to a certain industrial branch, the probability to need some amount of compressed air, the size of the site and/or company or the product produced. The probabilities for each group need to be multiplied, yielding a product of several roughly independent variables and thus justifying the expectation to find approximately a log-normal distribution of compressor powers. As the log-normal distribution is a good approximation for a distribution of several multiplied random processes, it seems appropriate here. In a log-normal distribution, the logarithms of the variable are normally distributed. The distribution function is heavy tailed, indicating that large compressors (in terms of power) are less likely, but not unlikely. The log-normal distribution has two numerical parameters, one for shape σ and one for scale μ. Its pdf is given by:

$$f(x) = \frac{1}{x\sqrt{2\pi}\sigma} \cdot \exp\left[-\frac{(\ln x - \mu)^2}{2\sigma^2}\right]$$

for $x > 0$ and zero otherwise

Assuming this functional shape and using a least-square fit to derive the parameters best matching the compressor sales leads to the fitting curve illustrated by the dashed line in Figure 1. We observe a good quantitative agreement between the data and the used log-normal distribution. Thus it is possible to reproduce the information contained in the data sample approximately by providing the information on the used functional shape (i.e. a log-normal distribution) and the two parameters for this shape. The corresponding cumulative density function can be used to compute the share of the compressors that have a power below the specified value x.

After discussing this first idea of the function-based approach, we can now address the second idea in another example: an important factor affecting the number of objects in a stock and the energy demand is the age structure of the objects



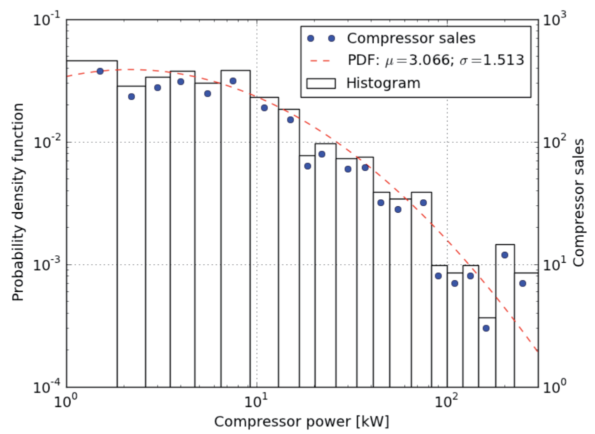


Figure 1. Fit of compressor sales by compressor power. Left panel: Aggregate number of compressor sales (right vertical axis), corresponding histogram and log-normal fit of the histogram data (left vertical axis). Right panel: Same data in a log-log diagram.

in stock. With regard to air compressors, there are no statistics available of the actual lifetime of air compressors in industry. Yet there are some indications on air compressor lifetimes in Radgen and Blaustein (2001) which suggest average lifetimes of 13 years for smaller compressors (power between 30 to 110 kW) and 16 years for larger compressors (power between 110 to 300 kW). While this information on lifetimes might be suitable to analyse average companies, one can observe that in practice sometimes air compressors remain considerably longer in operation. Therefore, it seems more realistic to use a range of different lifetimes by introducing survival probabilities instead of using a single fixed value. Weibull functions are known to approximate empirical survival probabilities quite well (see Bucher et al. 2011 and references therein) and have for example been used to estimate lifetime distributions of residential appliances (e.g. Lutz et al. 2011). The cumulative density function of a Weibull distribution can be described using the parameters k and T by:

$$F(a) = 1 - e^{-\left(\frac{a}{T}\right)^k}$$

For our case, this function describes how many compressors fail at the age of a. As we are interested in the share of compressors still in operation, however, we can compute the survival function $L(a)$ as:

$$L(a) = 1 - F(a) = e^{-\left(\frac{a}{T}\right)^k}$$

The parameter T has a simple interpretation: if the age of the compressors is equal to T, then about 1/e = 36.8 % of the initial compressors are still in operation. An illustration of the functional shape is given in Figure 2.

Though there is some uncertainty in determining parameters for the function, using the distribution function is clearly more realistic than assuming a fixed lifetime for all compressors. Using this kind of functional approach requires few additional assumptions on lifetimes, but it can considerably help to improve the quality of stock estimates. For practical applications, one way to obtain the relevant parameters could be to propose and discuss different sets of parameters with experts to identify the values best reflecting the situation the experts judge most likely.

Using these two ideas, we think that it is possible to improve the quality of energy-related stock modelling approaches and to make the results more transparent. To illustrate the approach further, we complement the above given examples by additional information in the next section and show how this modelling approach can be used to support the policy design process.

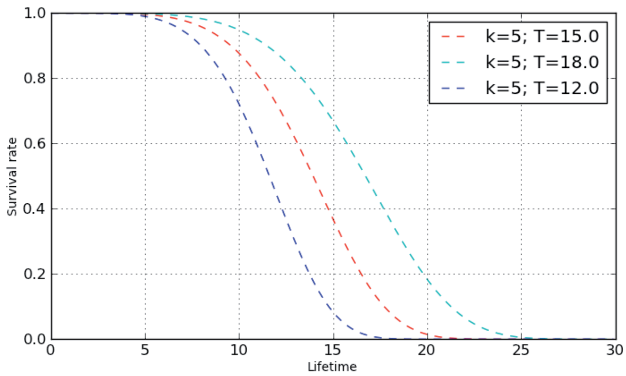


Figure 2. Survival as function of lifetime. Illustration of the survival function L(a) for the base case (curve in the middle) and the sensitivity analysis (curve to the left and right).

Application to industrial air compressors

GENERAL OVERVIEW

In the following, we illustrate the suggested stock modelling approach in a case study concerned with industrial air compressors in the European Union. As mentioned above, current stock models of air compressors, i.e. Radgen and Blaustein (2001), do not provide their entire set of input data and only used simple classes of compressors with average lifetimes and working hours. Our aim is go one step further by explicitly implementing, among others, a distribution of compressor power that is then explicitly combined with stock information. For this purpose, we use the first of the earlier discussed stock modelling approaches. Similarly to the study of Radgen and Blaustein (2001), we focus on air compressors between 1 and 300 kW, thus excluding larger compressor systems, but including some smaller compressors. Note that as the main purpose of this case study is illustration; we only provide a very simple, aggregated analysis. Though we try to provide parameters within realistic orders of magnitude, many are based on assumptions. Thus the results we present here require further validation.

The elements illustrated in the left segment of Figure 3 are necessary to determine the number and age structure of the air compressors currently used in industrial companies. The remaining elements in Figure 3 illustrate the calculation of energy demand based on the stock modelling results. We already discussed the capacity distribution and the determination of retired units above and will use them to calculate energy demand. The remaining elements will be discussed below.

An overview of the input data used for this analysis is provided in Table 1 along with sensitivity information used later on. As can be seen, only very little information is required to set up the stock model. Information on net production, growth rates, retired compressors and operating time is modelled by functions using estimated parameters as the quality of available data is not satisfying or no data is available at all (see next section). The capacity distribution of the considered compressors is based on the above provided fit of compressor sales.

STOCK MODELLING

As detailed above, the first kind of stock modelling approach requires knowledge about the net production of air compressors and on the retirement of the considered compressors. With regard to estimating net production, some data is available from EUROSTAT, detailing compressor production, exports and imports by different classes of compressors. However, a brief review has shown that net production (production + imports – exports) considerably fluctuates by unrealistic order of magnitude, both for different member states and for consecutive years (Obergföll 2012). Furthermore, data is sometimes inconsistent (e.g. yielding negative net production) and the number of produced compressors appears to be very high (net

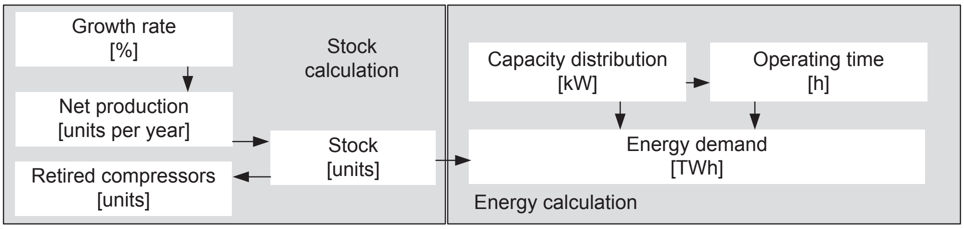


Figure 3. Elements considered in the case study. Left segment: Main elements used to calculate the stock of compressors. Right segment: Information on the calculation of energy demand.

Table 1. Overview of case study input data and data used for sensitivity analysis.

Information	Unit	Values	Sensitivity analysis
Net production	[number]	N = 25,000	Absolute change: ± 20%
Historic growth rate	[% per year]	g_h = 1 %	-
Future growth rate	[% per year]	g_f = 0 %	Absolute values: ±1%
Retired compressors	[function parameter]	T = 15, k = 5	Relative change of T: ± 20%
Operating time	[function parameter]	a = 1,500, b = 75 kW	Relative change: ± 20%
Capacity distribution	[function parameter]	μ = 3.066, σ = 1.513 (based on fit)	-

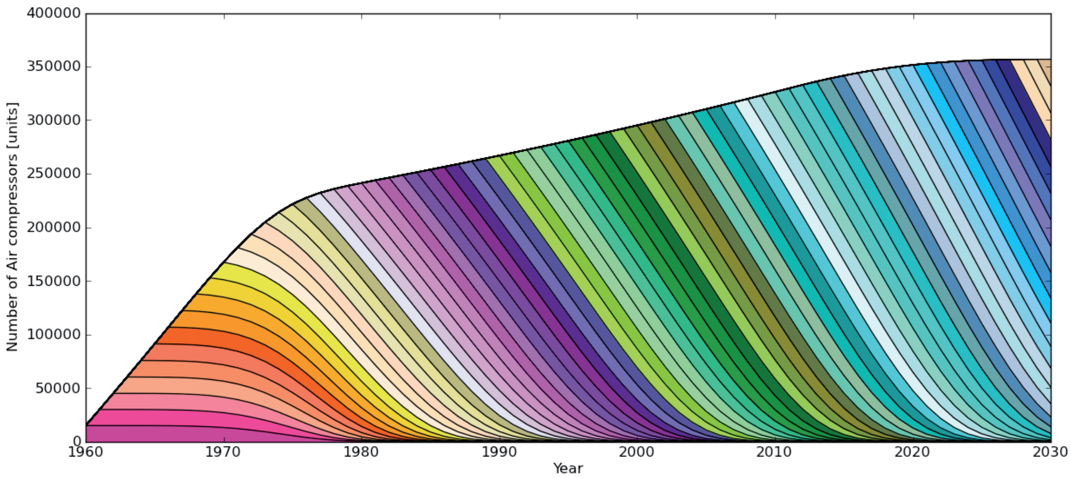


Figure 4. Stock of air compressors. Modelling results for the compressor stock between 1960 and 2030. Each colour shows the number of compressors still in operation that were produced in the same year.

production of reciprocating compressors is larger than 1 million units each year). Thus the statistics likely include other types of compressors than we intend to analyse here. For these reasons, we do not fit this data here, but assume a net production of air compressors, amounting to $N(s)$ = 25,000 units in the base year s = 2012. Furthermore, we assume that both a historic growth rate g_h (1 % p.a.) and the future growth rate g_f (0 % p.a.) of the compressor net production are constant and known, and that the net production $N(t)$ in the year t can be derived by:

$$N(t) = \frac{N(s)}{(1+g)^{s-t}} \quad \text{with} \quad g = \begin{cases} g_h, & \text{if } t \le s \\ g_f, & \text{if } t > s \end{cases}$$

Combining this information with the above discussed Weibull distribution for compressor lifetimes, the overall stock of air compressor is calculated by:

$$M(t) = \sum_{s=1960}^{t} N(s) \cdot e^{-\left(\frac{t-s}{T}\right)^k}$$

Applying this equation to a period from 1960 until 2030 provides us with Figure 4, which illustrates the number of compressors by their age structure. For our purpose, the most relevant area is the years beyond 2000. Thus the main purpose of modelling earlier years is to obtain a suitable age distribution of the compressor stock. The steep increase in the slope from 1960 has to be seen as the result of the growth-rate modelling approach rather than actually corresponding to the historical development. Yet it illustrates well how the stock is actually built over time. The rather homogeneous slope between 1980 and 2012 can be explained by the modelling approach of net production as well, as it reflects the steady increase in net production assumed earlier. Note that even though there is no increase in net production after 2012, it can be observed that the stock is still increasing until it finally reaches a plateau. Furthermore, it is worth mentioning that a certain share of the compressor built in 1960 for example is still in operation well after 1975. This effect cannot be considered when using stock models with fixed component lifetimes.

OPERATING TIME

While there appears to be general agreement that operating time increases with compressor capacity, estimates of average operating hours of industrial air compressors show a considerable degree of heterogeneity for various countries (see e.g. Radgen and Blaustein 2001, Gloor 2000). For our analysis, we use a simple linear model whose parameter can basically be derived by first asking about the minimum operating hours a of air compressors in industry, on the one hand, and by asking for the minimum compressor capacity that is typically running in full-time operation in industrial companies b, on the other hand. With these two parameters available, the annual operating hours $h(p)$ can be derived for any given compressor powers p in kW with (Figure 5):

$$h(p) = a + \frac{8760 - a}{b} \cdot p$$

Figure 5 shows the resulting graph for a minimum of 1,500 operating hours per year and a minimum compressor capacity with full-time operation of 75 kW.

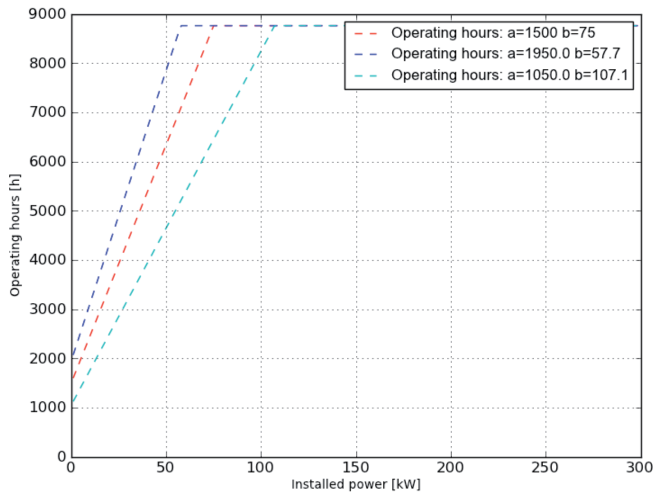


Figure 5. Operating time. Illustration of the assumed installed power of the air compressors for the base case (curve in the middle) and the sensitivity analysis (curve to the left and right).

ENERGY DEMAND

Combining the stock information, the capacity distribution and the information on operating hours allows calculation of energy demand $E(t)$ of the considered air compressors using the following equation:

$$E(t) = \sum_{s=1960}^{t} N(s) \cdot e^{-\left(\frac{t-s}{T}\right)^k} \cdot \int_{p=1}^{300} \left(\frac{f(p)}{F(300) - F(1)} \cdot p \cdot h(p) \right) \mathrm{d}p$$

The first factor in the integral describes the share of compressors with an installed power p. Note that the probability density function $f(p)$ has to be renormalised if only a certain segment of the probability density function is considered (here: installed power between 1 and 300 kW). The second factor is the actually installed power p and the third factor $h(p)$ describes the operating hours of the considered segment. Applying this equation to a sequence of years provides energy demand by age segment as shown in the left panel of Figure 6; as the capacity distribution remains independent of time, so far, energy demand has the same shape as the stock of compressors, as shown in Figure 4. Another representation of energy demand is provided in the right panel which structures overall energy demand by compressor capacity segments. It is worth mentioning that based on the compressor size distribution as provided in Figure 1, the share of compressors above 100 kW in the overall stock is well below 50 %. Nevertheless, due to the higher installed power and the higher operating hours of the larger compressors, they are responsible for about half of total energy demand.

SENSITIVITIES

As pointed out, the parameters used for the energy demand calculation are based on rough estimations. To analyse the effect of uncertainties related to the values of the parameters, we do some sensitivity analyses that can be easily carried out using this function-based approach. Figure 7 shows the effects of different changes in the input parameters provided in Table 1. The modelling shows that the assumed uncertainty in net production has a very substantial impact on the overall energy demand of the analysed compressors. A similar observation can be made for uncertainties concerning compressor lifetimes. On the other hand, a change in operating hours would not affect energy demand substantially. This can be explained by looking at the structure of energy demand by compressor size segment (Figure 6, right panel): Compressors with powers above 100 kW substantially determine energy demand. Changing parameters that mainly affect operating hours for smaller compressors will therefore only affect overall energy demand to a limited extent. With regard to future growth rates, one may note that the +1 % sensitivity is identical to the historic growth rate, thus energy demand is continuing to rise similarly as in the year before the base year. On the other hand, a declining market (-1 % per year) for air compressors only gradually reduces energy demand. Note that it is also possible to combine the different uncertainties into one plot to provide an overall corridor of uncertainty. Note further that the uncertainty intervals have only been chosen symmetrically for reasons of simplicity.

ENERGY FORECAST CONSIDERING POLICY MEASURES

After discussing the compressor stock and its energy demand, we can return to our initial idea of using the proposed stock model approach to analyse policy measures. As a baseline, we keep the above provided projection for energy demand, essentially corresponding to a “frozen-efficiency” scenario. We furthermore discuss two policy scenarios: in the first scenario (“fixed improvement”), we assume that all newly introduced compressors after 2012 have a constant reduced energy consumption corresponding to 90 % of the energy demand of the compressors from 2012. In our modelling approach, this translates into a reduction of the capacity of new compressors by 10 % (but without affecting their operating hours), thus:

$$\tilde{E}(t) = \sum_{s=1960}^{t} N(s) \cdot e^{-\left(\frac{t-s}{T}\right)^k} \cdot \int_{p=1}^{300} \left(\frac{f(p)}{F(300) - F(1)} \cdot \tilde{p}(s) \cdot h(p) \right) \mathrm{d}p$$

$$\text{with} \quad \tilde{p}(s) = \begin{cases} p \text{ for } s \leq 2012 \\ 0.9\, p \text{ for } s > 2012 \end{cases}$$

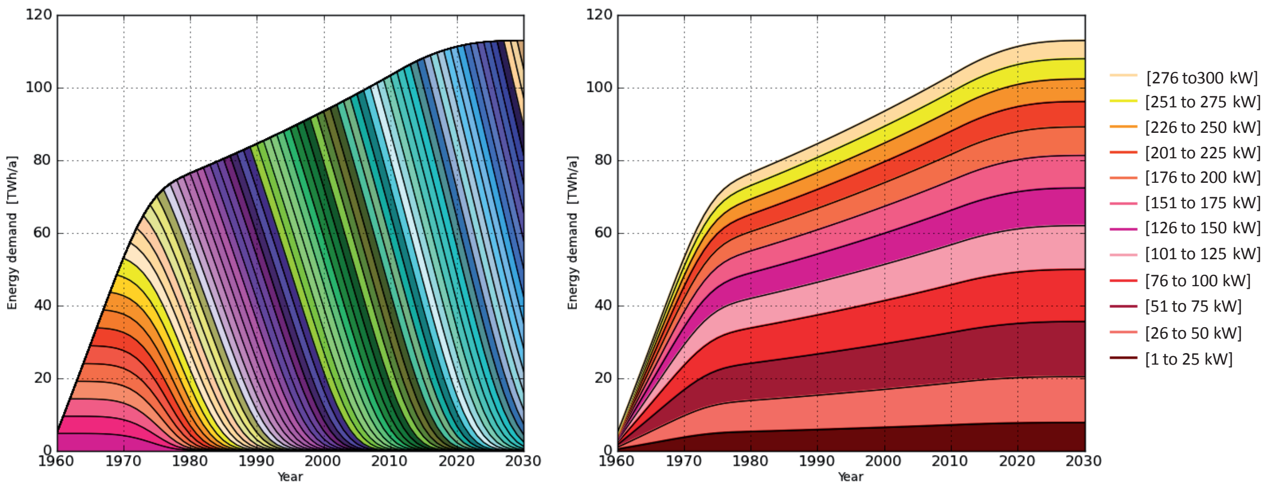


Figure 6. Energy demand development of the air compressors. Left panel: Energy demand due to the compressors produced in the same year (similar shape as Figure 4). Right panel: Energy demand by installed power. Large compressors (above 100 kW) are responsible for a considerable share in overall energy demand despite their comparatively low share in the overall number of compressors.

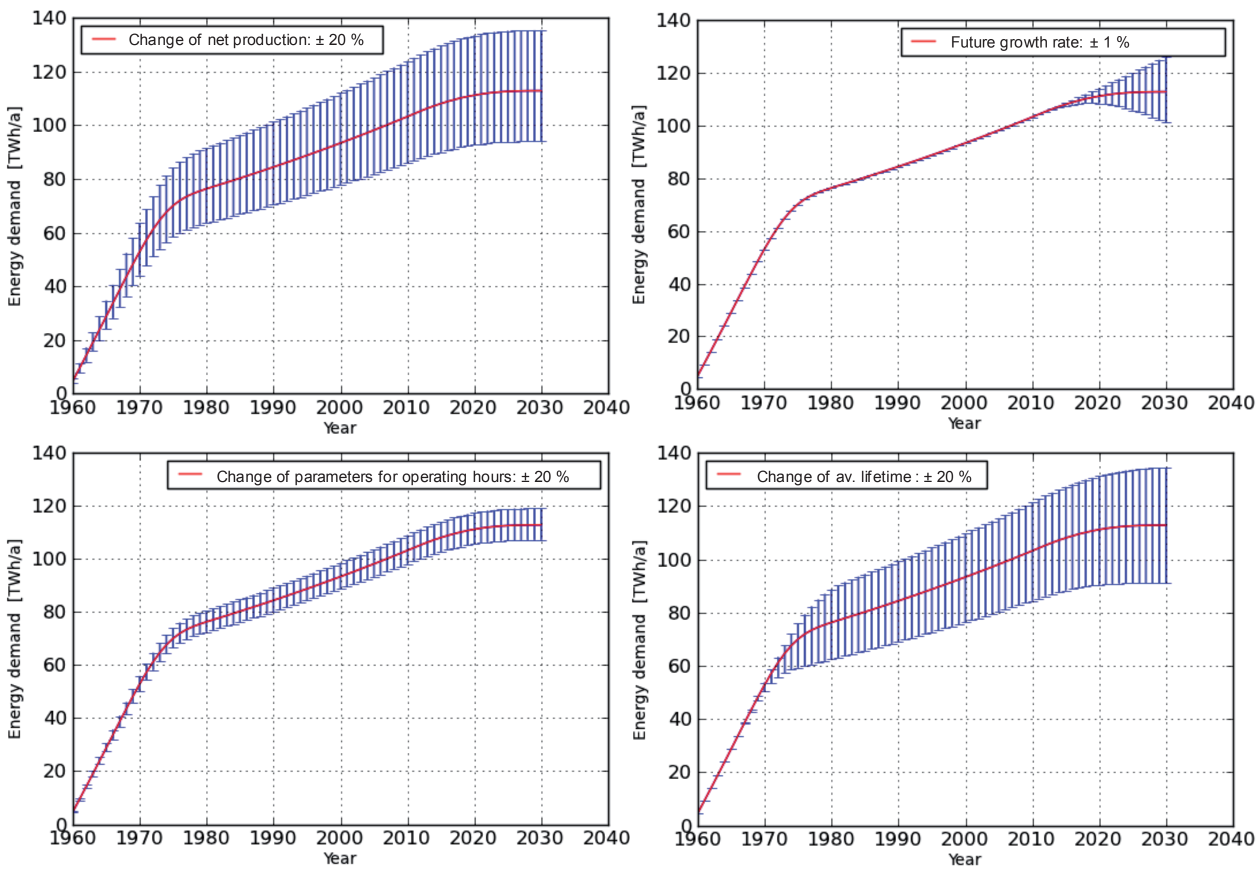


Figure 7. Sensitivity analysis. Upper left panel: Change of net production by 20 percent. Upper right panel: Change in energy demand after modifying the future growth rate. Lower left panel: Change of operating hours. Lower right panel: Change of assumptions on average lifetime for the compressors, considerably affecting energy demand, as well.

Such a scenario could for example correspond to defining minimum energy performance standards, where certain thresholds are fixed that are only revised after a certain period of time.

As a second scenario ("continuous improvement"), we assume a gradual improvement of 2 % per year after 2012 for new compressors, as compared to the compressors in the year before:

$$\hat{E}(t) = \sum_{s=1960}^{t} N(s) \cdot e^{-\left(\frac{t-s}{T}\right)^k} \cdot \int_{p=1}^{300} \left(\frac{f(p)}{F(300) - F(1)} \cdot \hat{p}(s) \cdot h(p) \right) \mathrm{d}p$$

$$\text{with } \hat{p}(s) = \begin{cases} p \text{ for } s \leq 2012 \\ 0.98\, p^{s-2012} \text{ for } s > 2012 \end{cases}$$

Such a scenario could for example represent a voluntary agreement scheme, obliging compressor manufacturers to improve the compressors or CAS every year.

The results of both scenarios are shown in Figure 8. Using the stock modelling approach, one can observe that the improvements from the second measure lead to higher reductions in energy demand after a certain period of time. While the energy demand of new compressors in 2017 is approximately equal in both scenarios, it is important to note that it takes another five years before both scenarios actually lead to the same energy demand. Nevertheless, the smaller but gradual improvements in energy efficiency from the second measure will eventually outweigh the larger improvements from the first measure in the long term. While both scenarios only serve for illustration, they underline the importance of considering the actual stock development when discussing different policy options.

Discussion

After presenting the model idea and a sample case study, advantages and drawbacks of this approach can be discussed: One major characteristic of the suggested approach is that it can handle both very detailed and very rough information. By reducing data to its most relevant information, it is possible to develop a proxy which can easily be used to analyse energy demand for various end-uses. As shown, such a functional shape with few parameters can also be used for quantitative computations when only little information is available, if reasonable parameter estimates can be provided. In both cases, the use of a few instead of many parameters can substantially increase the transparency of stock model calculations. Only two parameters (namely scale and shape) are needed to completely characterise the data used in the stock model. For the above given sample of compressor sales, for example, it is not required to provide 2 times 21 parameters (class definitions and values), but only the information that a log-normal fit with μ = 3.066 and σ = 1.513 was used. While the amount of original data in this example is very small, this approach can prove very beneficial if the sampled dataset is large. With regard to bottom-up energy demand models, for example, data handling can be a very time-consuming factor in the calculation if it has to be done in each calculation run. If the suggested approach is adopted in larger bottom-up models, it could be very beneficial as it reduces the amount of data handling in the modelling process. Instead of using the data in each run (including the necessary database operations), one might process the input data once and then only change the resulting parameters if the detailed input data is changed. Thus modelling efficiency can be increased. The numerical simplicity of the presented approach has for example been successfully used to model sales and stock of different vehicle drives, taking the large heterogeneity of car users explicitly into account (Plötz et al. 2012). Another advantage lies in the very easy analysis of sensitivities and uncertainties. If only a few parameters have to be adjusted instead of a whole dataset, sensitivity calculations can often be done more efficiently. With regard to uncertainties, one functional shape can also be replaced by another type of function. Furthermore, the small number of parameters and the explicit use of distribution functions make error analysis, both of numerical as well as analytical errors, much easier.

On the other hand, there are also some limits to this kind of modelling approach. First of all, the function-based approach

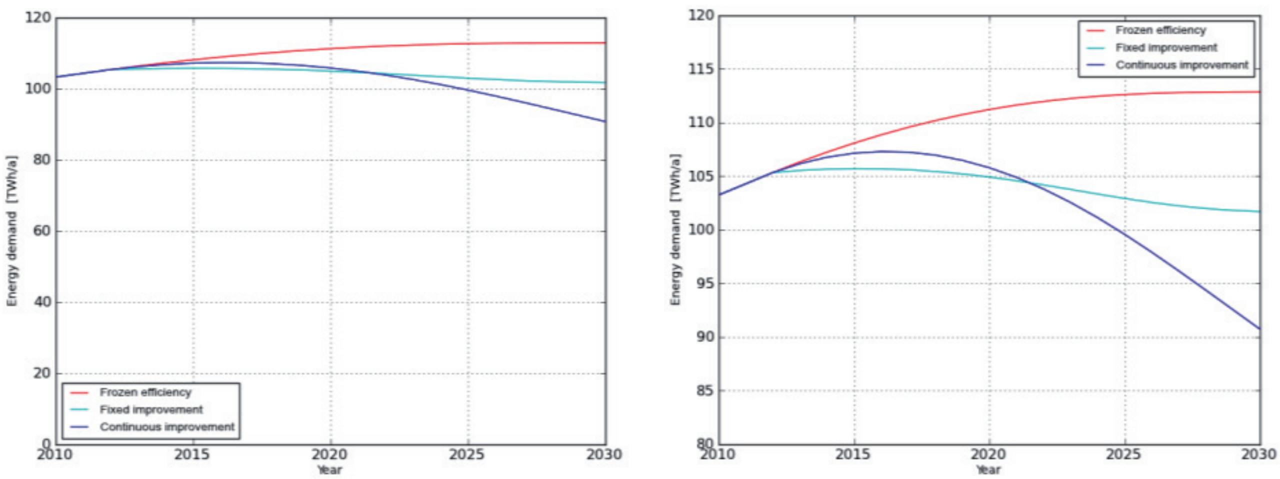


Figure 8. Scenario analysis. Left panel: Energy demand by CAS over time for three different (policy) scenarios. Frozen efficiency corresponds to the energy demand data as shown in Figure 6. Right panel: Zoom of the left panel. Note that the two scenarios with improvements do not cross until after 2022.

is mathematically more complicated than simple stock model approaches. Furthermore, fitting existing data requires caution and efforts to find a suitable functional shape. It is always necessary to confirm that the fit actually reproduces the input data sufficiently well, especially when translating discontinuous data with large segments into continuous functions. Therefore it is always advisable to check whether the functional shape is actually suitable for a subsequent use in a model, especially if values outside the fitting range are computed. However, significance tests and goodness-of-fit statistics are standard in virtually all scientific communities. In the above example, we limited our analysis to the power segment between 1 and 300 kW and we obtain a relatively steep fitting function. If you remove the limits and use differently inclined functions, the cumulated density function might provide a substantial number of compressors well above several MW, which can substantially affect the plausibility of the results. Furthermore, caution is required when analysing results: Even if results appear to be very detailed, it is essential to know which assumption the results are actually based on. This is especially true if parameters and functional shapes are estimated. Sensitivity analyses can help in this case to better understand the error related to such estimations.

The approach presented is certainly transferable to other fields of application such as electric motors or household appliances. If sufficient empirical data is available, probability density functions can be fitted. If data is lacking or of bad quality, one can again rely on estimates. However, the approach might not be useful for all cases, since distribution functions are only meaningful when the variable under consideration actually takes numerical values from a wide range of numbers as is the case with compressor power.

Conclusions

In this paper, we suggested a function-based approach to stock modelling, illustrated and discussed for the case of CAS in European industry. We think that this approach allows more transparent and more flexible results to be obtained, compared to classical stock modelling approaches. It may thus serve as a basis to better understand and evaluate the effects of different policy options on energy-efficiency improvements in the industrial sector. Furthermore, it helps to use, display, and discuss data in an easy and highly transparent way.

The purpose of the case study we presented was primarily illustrative. The proposed stock model could be designed with far more details. Possible extensions could, for example, include differentiating various types of air compressors, explicitly considering energy-efficiency improvements instead of using compressor capacity as proxy variables, or conducting the analysis for different countries or industrial branches.

With regard to further evaluating the benefits of the proposed function-based approach, it could be used in conjunction with expert estimates to gain a better understanding of the structure of various types of industrial applications. An especially interesting issue in this context is to evaluate to what extent simple functional approaches are actually accepted by experts and can serve to improve the quality of energy demand estimates. Another interesting option could be to integrate this approach into data-intensive bottom-up energy demand models for industrial applications. This could for example help to extend such bottom-up models by considering the heterogeneity of different end-uses and end-users while avoiding adding considerable additional amounts of input data to already data-intensive models. There are many and varied possibilities to further utilise and apply this suggested approach.

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