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Useful energy balance for the UK: An uncertainty analysis☆

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HIGHLIGHTS

- Uncertainty of with Final and Useful energy statistics is explored for the first time.
- Data about end-use conversion efficiencies is collected and updated.
- In the UK, The average Final to Useful conversion efficiency is of 67%.
- A large share of Useful energy consumption (85%) has an uncertainty below 25%.
- Internet of Things will improve end-use energy statistics, including Useful Energy.

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ABSTRACT

The use of Useful energy as an energy indicator for sustainability and energy efficiency policy making has been advocated for since the 1970s. Useful energy is the energy delivered by conversion devices in the form required to provide an energy service. This indicator has not been employed mainly because of concern over the reliability of the underlying data, however its uncertainty has never been quantified. This study is a first attempt to rigorously quantify the uncertainty that is associated with Final and Useful energy balances. A novel methodology based on a Bayesian approach is developed, previously unpublished data about average end-use conversion device efficiency is compiled and the Useful energy balance of the United Kingdom is calculated. The uncertainty analysis shows that the largest source of uncertainty is the allocation to energy end-uses, where the uncertainty of the energy flows goes from a median value of 5% to one of 34%. Useful energy consumption for transport and for heating has low uncertainty (4–10%) and overall, 85% of consumption has uncertainties below an acceptable 25% threshold. Increased availability of energy consumption sensing technology will enable the improvement of end-use energy statistics. If governments and statistical offices seize this opportunity, Useful energy has the potential to become an important indicator for the development of energy efficiency policies and thus help stimulate policy action in end-use sectors.

1. Introduction

The need to reduce global green house gas (GHG) emissions has induced governments to implement a number of policies aimed at reducing energy consumption. The IEA estimated that the share of global energy consumption being affected by efficiency and conservation policies rose from 14% in 2005 to 27% in 2014 [1]. The successful implementation of efficiency policies requires appropriate indicators and energy statistics in order to track progress, to prove additionality and to set targets [2]. Two example statistics used for these purposes are the vehicle stock fuel efficiency (l/100 km) [3,4] and the energy requirement for heating and cooling of buildings (kWh/m^2) [5].

All current energy efficiency indicators are based on measures of Primary or Final energy. Since the 1970s, academics [7] have argued in favour of measuring Useful energy, for its use as an energy indicator. Fig. 1 illustrates the relationship between three ways in which energy is measured. Primary energy refers to the energy that is extracted from nature, such as the chemical energy of coal, or the kinetic energy of water streams [8]. Primary energy is mostly converted into energy carriers (eg. electricity, gasoline) which are purchased by final consumers. The total amount of energy purchased is referred to as Final energy. Energy carriers are employed for different end-use applications (*end-uses*), such as cooking, heating spaces or the provision of movement. The energy for each end-use application is provided by a *conversion device*, which transforms energy carriers in the desired energy form (e.g. thermal, kinetic, and electromagnetic energy). The output

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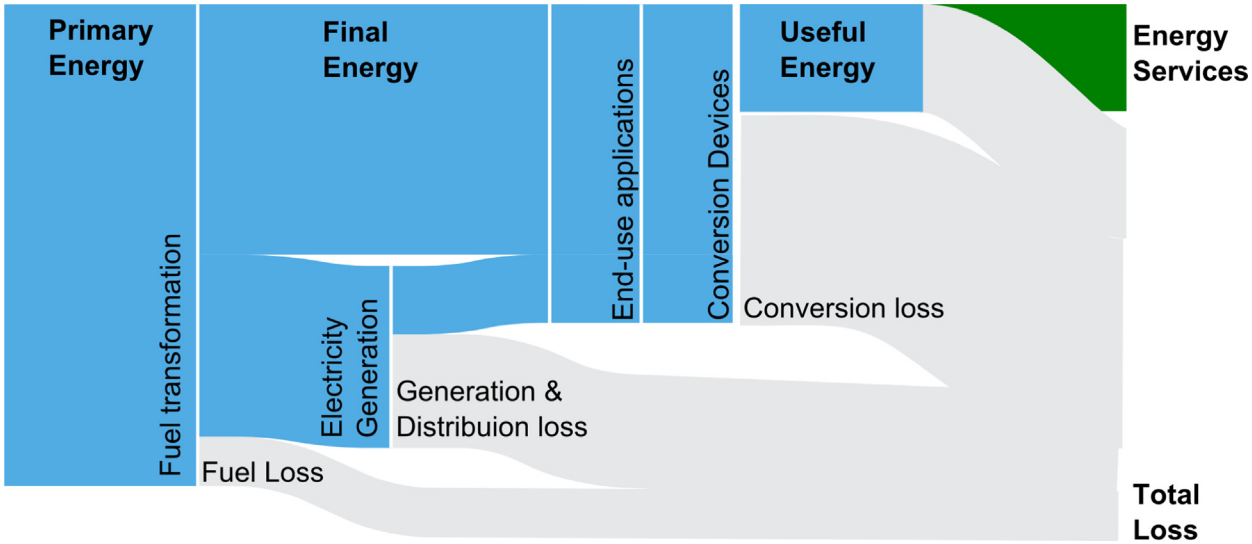

Fig. 1. Schematic of the flow of energy from Primary,through Final, to Useful, adapted from [6].

energy from conversion devices is referred to as Useful energy. Useful energy is also the last form of energy that can be measured in energy units before the delivery of an energy service and it can diverge substantially from Final energy. For example, roughly 25% of Final energy delivered to road transport is converted to Useful kinetic energy, in contrast, over 300% of the Final energy delivered to heat pumps is converted to Useful thermal energy.

There are at least three reasons why understanding Useful energy consumption is important. First, there is skew towards supply side measures in climate mitigation plans [9] at the expense of demand-side measures. One of the reasons for this is that Primary and Final energy accounting practices are well established and a multitude of metrics are available for policy design. Useful energy accounting, with its focus on the demand side of the energy system, can provide additional indicators for the development of energy efficiency policies. Since the availability of indicators for policy design and evaluation are key to policy development, Useful energy accounting could help bridge the gap between supply side and end-use side policy action.

Second, Grubler [10] highlights that a key limitation in the understanding of long term energy transition has been the lack of Useful energy data and that the reliance on Final and Primary energy figures might have distorted our understanding of past energy transitions.

Third, researchers in the field of exergy economics have been exploring the impact of Useful energy on economic growth [11], claiming that the addition of Useful energy time series can better explain economic growth compared to the traditional economic production factors of capital and labour.

Despite these benefits, only few Useful energy accounts exist in official publication and academic studies. One of the reasons for this is the concern over the reliability of Useful energy estimates [12], as exemplified by the following statement in the 2014 digest of United Kingdom energy statistics: “Statistics on Useful energy are not sufficiently reliable to be given in this Digest; there is a lack of data on utilisation efficiencies and on the purposes for which fuels are used” [12]. However, the recent increase in demand side energy efficiency policies has lead to an increase in the quality and quantity of energy end-use statistics in many countries. A questions arises from these developments: is the existing data sufficient to paint an accurate picture of Useful energy consumption?.

This study aims to answer this question by achieving two objectives: (a) to provide a methodology to estimate the uncertainty of Useful energy calculations, and (b) to test this methodology with the application to the United Kingdom’s energy system. In the next section, a review of the literature surrounding Useful energy accounting is provided. In Section 3 the model employed to calculate Useful energy and to estimate its uncertainty is described while Section 3.3 focuses on the data relevant to the UK. In Section 4 the results of the study are displayed and discussed, and Section 5 draws conclusions and suggests avenues of further research.

2. Previous work

The relevant literature is split in three parts. First, past examples of official Useful energy balances are presented along with the current practices used to estimate the quantity of energy used in each end-use application. Second, literature from the Societal Exergy Analysis field is summarised and compared to standard Useful energy accounts. Third, the literature dealing with the theoretical framework required for uncertainty analysis of top down statistics is outlined.

2.1. Useful energy statistics

Useful energy is used in energy demand modelling at various levels. For example, it is used at a global level in the World Energy Model [13] and at a sectoral level in the UK [14]. The metric is also often used in facility level analyses [15], especially for air conditioning systems where end-use efficiencies of different technologies have large variations [16]. However, Useful energy consumption is seldom measured directly because it would require the measurement and recording of each of the various energy-using devices. In addition, no monetary transaction is usually involved with the conversion from Final to Useful energy, therefore its estimation cannot be based on existing accounting practices as is the case for Final and Primary Energy [6]. Instead, Useful energy is calculated from Final energy statistics with the addition of two pieces of information: the split (or allocation) between end-use applications of energy, and information on the average conversion efficiency of each end-use application. Eq. (1) summarises the simplest Useful energy calculation method.

$$U = F\ \phi\ \eta \tag{1}$$

where U is Useful energy, F is Final energy, ϕ is the allocation vector that contains information on the split of energy end-uses, and η is the average conversion efficiency.

The European statistical office (EUROSTAT) attempted to estimate Useful Energy balances for member countries in the period between 1975 and 1988 [17,18]. The allocation of energy to various end-uses was completed for three broad sectors (Industry, Transport and

Buildings) using proxy data such as surveys of energy uses, the physical form of the energy products and expert knowledge of the energy uses in each sector. The average efficiencies were determined for about 30 devices based on unspecified "studies published by energy technicians and engineers". More recently, Useful energy accounts have been compiled at an European level [19,20], but only for the provision of space heating and cooling.

Outside Europe, the Brazilian ministry for mines and energy commissioned Useful energy analyses for the years 1984, 1994 and 2004 [21]. These studies had two aims: first to analyse separately the structure of energy consumption and the development of energy efficiency; and second to compute the energy saving potential from improved conversion efficiency. The authors employed various government-led surveys to assess the allocation of energy to end-uses while conversion efficiencies were estimated directly by the authors (without a clear methodology). Both these studies are well documented and analyse the entire energy system, but unfortunately they have been discontinued.

De Stercke [22] compiled a database containing estimates of Useful energy and Useful exergy for 15 countries in the period between 1960 and 2009. He employed IEA data as a starting point and used estimates by Nakićenović in 1996 [23] on the split of energy consumption to the various end-uses, whenever country specific data was unavailable. Data on conversion efficiencies found by past studies was used to define an empirical exponential function relating the efficiency of various devices with GDP to fill the gaps for years and countries without available data. This study has the benefit of providing a time series of Useful energy consumption for a group of countries, however gross approximations were required to fill the large data gaps present in terms of conversion efficiency and energy end-use split.

There are currently no official Useful energy balances being published by governmental agencies. One of the reasons for this discontinuation in Europe and in Brazil is the uncertainty associated with the estimates. In fact, as early as in 1979, the statistical review of UK energy stated estimates of Useful energy were desirable, but they were not published because they were deemed too unreliable [24]. However, official statistics on the breakdown by energy end-use, one of the key ingredients for Useful energy calculation, are becoming more common and refined thanks to their use in energy efficiency policies, as is discussed in following section. To quantify the effect of these improvements, an assessment of current Useful energy statistics is necessary.

2.1.1. End-use energy statistics

The IEA records that at least 14 countries provide end-use breakdown in the residential sector [25] while Enerdata provides the breakdown for all EU member states [26]. This data is compiled because the definition of some efficiency indicators require a disaggregation of energy consumption by end-use, for example the space heating requirements of dwellings, measured in kWh of space heating per m^2 [2]. The costs of gathering extra data on energy end-uses is justified by the avoided cost that would be incurred due to bad policy design and evaluation.

The reliability and accuracy of end-use statistics depends on the data gathering methodology. National statistical offices use different methodologies which can be categorised as follows.

- **Metering/Auditing** the breakdown can be measured directly by installing sub-metering equipment in buildings. This enabled a high resolution understanding of energy use by each type of appliance and end-use, as done for many EU countries [27–29]. In the industrial sector, this type of collection methodology is better described as an energy audit, where the performance of equipment and processes are measured by visiting experts. While there are several benefits to this methodology, its costs are high meaning that the sample size and frequency of the metering are often low [30].
- **Direct Survey** End-use energy breakdowns can be estimated using a survey that directly asks for the breakdown. This method assumes that the respondents are technically literate and have access to detailed data on their energy consumption [31]. Therefore, this methodology is only relevant to the industrial sector and possibly to buildings that employ an energy manager or an energy management system.
- **Engineering Models** Engineering models require information on a representative sample of buildings or of industries and a calculation method to estimate the breakdown of energy consumption. The input data required quantitative information on building physics (e.g. U-values, floor area, type of process technology) and energy using equipment. The detail and accuracy of the physical model is constrained by the resolution of information provided by the stock survey [32]. Such surveys are common for the residential and commercial sector, where governments need information on buildings for non-energy related purposes. For the industrial sector, engineering models break down energy consumption by end-use based on industrial equipment and process stock and efficiency. These models are usually not based on public surveys but instead are either informed by propriety databases [33] or by adhoc academic studies [34].
- **Statistical Models** This method is similar to the method described above in terms of data requirements and quality. However, instead of calculating the energy consumption based on physical relations, a regression analysis between input variables and end-use consumption is used. The regressions are calculated using historical data [35] on energy end-uses. For the industrial sector, statistical models can be used to model the cross-cutting energy requirements such as lighting or space heating [36].

The methods and sample sizes used to estimate the breakdown of energy end-uses have an impact on the reliability of the resulting statistics. However, the uncertainty associated with these estimates is seldom quantified or even assessed. This undermines the robustness of the end-use statistics, and of the study results.

2.2. Societal exergy analysis

One field that has expanded the concept of Useful energy is field of societal exergy analysis, which aims to characterise the energy efficiency of societies at different scales, sectoral, national and global [37]. Exergy rather than energy is used because it is believed to further describe the quality of energy consumption compared to energy metrics [38]. Estimates of the overall Primary to Useful exergy efficiency for different societies range between 10% and 30% [39].

Different methods are used in this field and the differences are well summarised in a recent review paper [37]. Eq. (2) describes how the total Useful exergy of a society (E_U) is calculated in most articles [40],

$$E_U = \sum F_{sfe}\ \eta_{sfe}\ \epsilon_{sfe} \tag{2}$$

where η is the end-use conversion efficiency, ϵ is the exergy factor and F is Final energy. The index s, f, e refer respectively to the sector, fuel and end-use of energy. This equation contains one further efficiency term (ϵ) compared to the standard Useful energy estimation method shown in Eq. (1). Cullen and Allwood [41] argue that better insights are available by distinguishing the technical sub-systems that form the energy system. To this end, they introduce the concept of "conversion device" and "passive system". The former are the ensemble of technologies that convert Final energy into Useful energy (eg. engines, boilers) while the Passive Systems dissipate Useful energy in order to deliver a energy service (i.e. vehicle body, building frame). Since conversion devices are well defined technical systems, it is easier to estimate their efficiency as well as their improvement potential [42]. According to their framework, Useful exergy is therefore better estimated as shown in Eq. (3),

$$U = \sum F_{sfd}\ \eta_{sfd}\ \ \epsilon_{sfd} \tag{3}$$

where all symbols retain their meaning and index d refers to the conversion device undertaking the energy conversion. The Useful energy/exergy results obtained in this field are often affected by the lack of robustness and reliability dictated by the numerous assumptions and estimates required. The following issues affect the reliability of the results.

- The allocation to end-use applications is often performed by a combination of data and educated guesses, without systematic and comparable methodology being put in place.
- The estimation of average conversion efficiencies employed are often quoted from previous work with minor adjustments. There is little focus on efficiency data gathering while there is a lot of reliance on expert judgement.
- The calculation of the exergy factors for each end-use requires estimates of average environmental and process conditions. However, there is very limited information on the average temperatures of the various processes.

While these issues have been recognised by members of the research community [37], the impacts of these assumptions on the results uncertainty has not been quantified yet.

2.3. Uncertainty in useful energy estimates

The topic of data uncertainty in energy statistics is not often discussed in academic debate. Macnick [43] contributed by highlighting the lack of attention given to uncertainty in energy statistics published by international organisations and stated that this might undermine the credibility of studies that employ this data. The long established practice of Primary and Final energy accounting by governmental agencies in the developed world means that statistical differences in energy balances are always below 0.5% and that the uncertainty associated with these estimates is deemed to be less than 5% [44,12]. The same cannot be said about Useful energy and exergy accounts [37], yet there is no established methodology to quantify the uncertainty of the results.

Fortunately, further insights on how to treat uncertainties in large systems can be gained from other fields such as Material Flow Analysis (MFA) [45]. Uncertainty can be of two types: epistemic or aleatory. The former refers to uncertainty due to lack of knowledge about the true value of a parameter, while the latter refers to the uncertainty due to the intrinsic randomness of a phenomenon [45]. For energy statistics, uncertainty is solely epistemic since energy flows in an economy have one true value, but there is uncertainty about this value due to knowledge imperfection.

Conventional approaches to uncertainty quantification and analysis [46] are less relevant here because they focus on repeatable processes such as measurements in experiments or survey answers. In contrast, the collection of national level energy statistics is a non-repeatable process. “Single-sample” uncertainty assessment techniques in use since the 1950s [47] aim to quantify the uncertainty of a given non-repeated measurement, but depend on empirical techniques such as auxiliary calibration experiments. These have no equivalent in assessing uncertainty in national statistics, where uncertainties are quantified through techniques such as expert elicitation and pedigree matrices. Therefore, the best way to analyse the uncertainty of this type of data is through a Bayesian framework using Monte Carlo methods [48]. In this framework, the uncertainty of a parameter is defined using probability distributions representing the degree of belief of that parameter. Bayesian approaches have been gaining momentum in studies that analyse the uncertainty of highly aggregated systems. For example, this theoretical framework is used in national and global level material flow analyses. Laner et al. have reviewed many possible techniques for uncertainty evaluation of MFAs [45] and developed a framework for data quality evaluation and uncertainty propagation which is based on the quantification of prior knowledge using a Bayesian framework [49,50]. Gottschalk et al. [51] discussed a Bayesian approach to MFA, and Cencic and Frühwirth [52] applied this to data reconciliation for simple linear models. Lupton and Allwood have introduced a general recipe for the application of the Bayesian framework to MFA and applied it to the global steel supply chain [53]. Also the techniques prescribed by the IPCC for GHG accounting are based a Bayesian framework since governments are asked to provide confidence intervals for their emission estimates [54].

In summary, two factors play in favour of the revival of Useful energy accounting. First, the introduction of energy performance standards mean that the efficiency of most energy-using products is now measured. This means that accurate year on year estimates of average end-use efficiency only require a stock model and sales data by efficiency category. Second, the ease of information gathering brought about by the ubiquity of sensors might further decrease the cost and increase the accuracy of end-use energy consumption surveys. Therefore, Useful energy balances might become more feasible and reliable. Within this context, this study develops a methodology drawn from other fields, to quantify the uncertainty of Useful energy in a country that has a wealth of publicly available energy statistics: the United Kingdom.

3. Methods

This section outlines the methods used for this study in three parts. First, the general methodology to disaggregate Final energy consumption and to compute Useful Energy is presented and terminology is introduced. Second, the uncertainty quantification techniques and the probabilistic model is described. Third, the data sources used to analyse the UK’s Useful energy consumption and its uncertainty are listed.

3.1. Useful energy calculation

Useful energy is calculated by multiplying Final energy consumption by the end-use conversion efficiency with the efficiency (η). Final energy can be disaggregated in terms of energy carrier f (e.g. Coal, Electricity, etc.), sector s (e.g. Industry, Residential), end-use e (heating, lighting, etc.), and device d (e.g. electric motor, boiler, etc.). Hence, Useful energy is calculated using Eq. (4).

$$U_{fsed} = F_{fsed}\quad \eta_{fsed} \tag{4}$$

Standard energy balances provide Final energy consumption statistics disaggregated in terms of energy carriers and sectors ($F_{f,s}$). Therefore, two allocation matrices ϕ and θ are needed before the Useful energy calculation can be made. Matrix ϕ allocates Final energy to each end-use application. For example, it can specify that Coal in the residential sector is used 80% for space heat and 20% for hot water. Matrix θ allocates Final energy to the specific conversion device used for each end-use. For example by specifying that 40% of oil used for mechanical energy in road transport goes to petrol engines and 60% to diesel engines. Eq. (5) summarises the relationship, where the superscripts indicate that there is a matrix for each of the indicated categories.

$$F_{fsed} = F_{fs}\quad \phi_{fs}^{(e)}\quad \theta_{fse}^{(d)} \tag{5}$$

In the following sections, the rationale behind the categories employed is described.

3.1.1. Final energy

National energy balances (such as those published by the IEA [55]) containing data on Final energy consumption split by economic sectors and by energy carriers are used to define F_{fs}. Energy carriers. These are classified based on their physical state in the following categories:

Table 1
List of end-use categories used to classify end-uses for all sectors.

End Use Category	Description
Process Heat - Direct	Energy applied directly for material processing (cooking, blast furnace, etc.)
Process Heat - Indirect	Energy delivered through an intermediate mean, usually steam
Space Heat	Energy used to maintain comfortable temperature inside buildings
Hot Water	Energy used to increase water temperature for hygiene and comfort
Space Cooling	Energy used to maintain a comfortable temperature inside buildings
Process Cooling	Energy used to decrease the temperature of materials below ambient (refrigeration)
Mechanical	Energy used to deliver Useful work (pumping, motion etc.)
Illumination	Energy used to the illumination of buildings and streets
Information, Communication, Entertainment	Energy used for computing power, and for communication and control

Liquid fuels, Gas, Coal, Solid Biomass and Waste, Electricity and District Heat (DH). Grouping energy carriers by physical state has the benefit of allowing a better match with specific conversion devices technologies.

Nine economic sectors categories used by the IEA are used in the study: Industry, Residential, Services, Agriculture/Fishing/Forestry (AFF), Road Transport, Rail Transport, Navigation, Aviation, and Pipeline Transport.

3.1.2. Sectors to end-use

Energy end-use statistics are used to define the ϕ^{e}_{fs} matrix which allocates Final energy to the various end-uses. To define this matrix, a coherent definition of end-use categories is required. End-use statistics are compiled at a sectoral level thus the categories employed are often sector specific. A cross-sectoral analysis requires comparable end-use categories for all sectors, while still being sufficiently specific about the end-use of energy. Since these two requirements are often at odds, a judgement is required in the defining the end-use categories employed. The German Energy Statistics Office provides a good starting point, as it employs end-use categories that facilitate a compromise between the two needs [56]. Table 1 lists and describes the nine end-use categories employed in this study. The only modification of the German definition is the split of the Process Heat category in Process Heat Direct and Process Heat - Indirect to fit the data available for other countries.

3.1.3. End-use to conversion device

The allocation matrix $\theta^{(d)}_{fse}$ describes the share of energy converted in a specific devices for a given combination of sector, energy carrier and end-use. The definition and classification of energy conversion devices used in this study is based on the work by Cullen and Allwood [42], with only one modification. Those authors distinguish four types of burners based on the type of fuel they use. While there are technical differences between these categories, there are further differences between the mode of combustion, that is, on whether the combustion occurs within a boiler or directly on the product to be heated. This is because the efficiency of the boiler depends on both the combustion efficiency and the heat exchanger design; while for direct combustion, only the former matters. Since the framework used in this analysis enables the distinction of energy flows by fuel, it is best to classify the devices only on their technical differences: direct combustion versus indirect combustion. Table 2 lists and describes the conversion devices employed in this study.

3.1.4. Conversion efficiency

The conversion efficiency of each device must represent the average efficiency for a device using a given energy carrier, in a given sector to deliver a specific energy service. The definition of efficiency depends on the system boundary chosen. In this instance, the boundary is limited to the first form of energy in the Useful form. For example, for an electric motor, the mechanical energy measured at the shaft is considered the device output; even though energy may be used further used in other devices such a driving a fan. The output from the conversion devices is classified in five Useful Energy categories derived from Cullen et al. [41]. These are: Motion, Heating, Coolth, Illumination, Information.

Table 2
Description of the energy conversion device categories employed, adapted from Cullen and Allwood [42].

Conversion Device	Description
Spark Ignition Engine	Spark ignition Otto engine (car, generator, machinery)
Diesel Engine	Compression ignition diesel engine (truck, car, ship, train, generator)
Gas Turbine	Jet engine for aircrafts, gas turbines for mechanical drive (industry, pipeline compressors)
Electric Motor	AC/DC induction motor (excl. refrigeration)
Boiler	All fuels to: Space Heat, Hot Water, Process Heat-Indirect
Electric Heater	Electric resistance heater, electric arc furnace
Burner	Process Heat Direct from fuels. All uses of DH
Cooler	Refrigeration, air conditioning, air separation
Light Device	Lighting (tungsten, fluorescent, halogen, etc)
Electronics	Computers, televisions, portable devices

Data on the average efficiency of conversion devices is seldom found in either official statistics or academic literature. When no information is available, average efficiencies must be estimated using other sources. These include: technical equipment surveys, device performance databases; and device performance data found in manufacturer's catalogues. Whenever possible and appropriate performance data is collected for a large number of conversion devices. This data is analysed to obtain a range of efficiency values as well as to determine the major trends that influence a device's efficiency (e.g. power rating, technology type).

3.2. Uncertainty analysis

Three steps are used to assess uncertainty in this analysis. First, the uncertainty associated with each model parameter is quantified and described. Second, a probabilistic model is defined. Third, the uncertainty is be propagated in the model to assess the uncertainty of the Useful energy consumption.

3.2.1. Uncertainty estimation

Epistemic uncertainty is routinely quantified in various fields such as engineering modelling [57], scientific computing [58], and safety assessments [59]. Two widely used methods for uncertainty quantification are expert elicitation and the pedigree matrix. Expert elicitation techniques are designed to formally interview experts in the field who possess in depth knowledge of the parameter being studied. This is used in risk assessment and in technological forecasting studies [60]. The pedigree matrix technique enables the consistent quantification of the uncertainty of the available data by assessing it against multiple quality dimensions. This method is mostly used in Life Cycle Inventory [61] and in MFA [50]. In addition to these primary methods, statistical agencies can provide confidence intervals or uncertainty ranges for their published statistics.

In accordance with the IPCC guidelines, in this study uncertainty is defined as two times the coefficient of variation. This definition enables the uncertainty (Y) to be intuitively expressed as a percentage (e.g. ±Y

%).

3.2.1.1. Energy balance. Information on the uncertainty of energy statistics is rare. However, the 2006 IPCC guidelines on GHG inventories [54] advise Annex I countries to perform uncertainty analyses on their emissions. Since most of the energy system relies on fossil fuels, this data can be used to inform the uncertainty of energy statistics. Uncertainties are estimated by staff working in the reporting institution or by appropriate experts, for each energy carrier in each sector. Emission uncertainties are the combination of *emission activity*, which represents the physical quantity of fuel burnt, and of the carbon *emission factor* which represents how much CO_{2eq} is emitted by the combustion of one physical unit of fuel. The carbon emission factors are related to the heating values of the fuels since both are a function of the fuels chemical composition, and sometimes emission factors are calculated from calorific value data [62]. Therefore, it is assumed that the uncertainty of the calorific value is equivalent to that of the emission factor. Calorific values are easier to calculate than emission factors and are measured more often due to contractual needs. Hence the assumption is deemed conservative. The activity (A) and the emission factor (EF) probability density functions are combined to determine the overall emission intensity uncertainty (Y_e), as shown in Eq. (6)

$$Y_e = \frac{\sqrt{\mathrm{Var}[A + EF]}}{\mathrm{Exp}[A + EF]} \tag{6}$$

Knowing the probability distributions which describes these uncertainties it is possible to determine the probability density function of aggregated fuel categories. The uncertainty is assumed to follow a lognormal distribution because energy consumption cannot be negative. For electricity, the uncertainty in consumption derives from measurement error, since electricity network must always balance. Therefore a value of 0.5% is appropriate since this is the standard for electricity meters in the EU [63]. For district heating, an uncertainty of 3% is assumed since it represents typical metering accuracies [64]. The data on the variance of each fuel-sector combination is used to inform the probabilistic model of $F_{f,s}$.

3.2.1.2. Allocations to end-uses and devices. Energy end-use statistics collected using the methods outlined in Section 2.1.1 result in an allocation vector of proportions α_e for each energy carrier and each sector, such that

$$\sum_e \alpha_e = 1 \tag{7}$$

Statistical agencies rarely provide uncertainty estimates for their published values, and when they do, it is a single value (as reported in [65]). However, most end-use energy data is sourced from energy consumption models which provide interpretation and quantification of uncertainty in their input parameters and in their outputs. Given the lack of official figures, it is necessary to make use of expert judgement for the quantification of the uncertainty (Y) for each allocation.

Describing the uncertainty of an allocation is, perhaps surprisingly, not straightforward. For example, assume we have 100 MJ of energy split into three parts of 80%, 17% and 3%. What is the meaning of a 10% "uncertainty"? Intuitively, it is expected that all shares vary by 10%. That is, the biggest from 72 to 88 MJ, the middle one from 15 to 19 MJ and the smallest from 2.7 to 3.3 MJ. However, this is not possible. To see why, consider that the smallest share reduces to the minimum expected, from 3 MJ to 2.7 MJ. The other two shares must increase by a total of 0.3 MJ. Even if all of this increase went to the 80 MJ share, that would still be only a variation of 0.3/ 80 = 0.4%: much less than the expected variation. Conversely, if the largest share were to increase by 10% the corresponding change in the smaller shares would be bigger than expected.

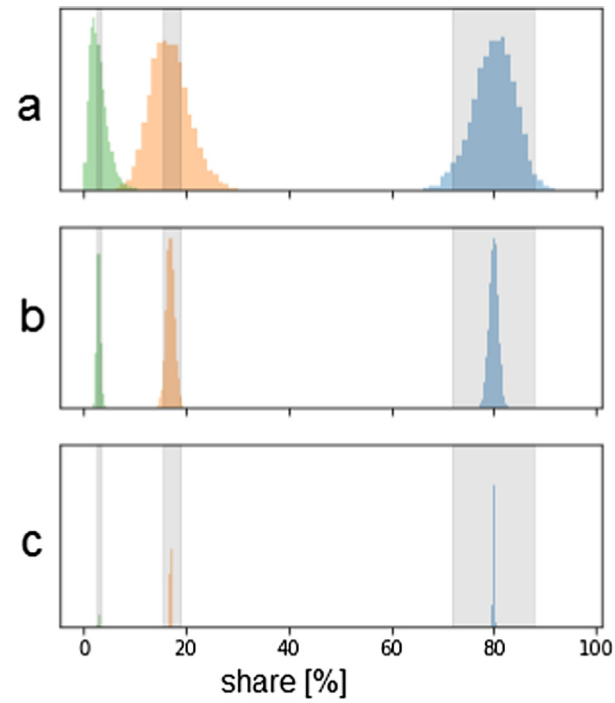

Fig. 2. Comparison of probability distributions from a Dirichlet distribution with input parameters $\alpha_e = [0.8\ 0.17\ 0.03]$ using three different interpretations for an uncertainty of 10%. In cases **a**, **b**, and **c** the 10% relative uncertainty is applied is applied respectively to the smallest, mid and largest input parameters. The shaded bands show the ± 10% range relative to each share which is in line with the most intuitive interpretation of uncertainty.

Because it is not possible to have "10% uncertainty" on all parts of the allocation, a choice about how to interpret the uncertainty must be made. At the same time, there is no information about the specific probability distributions describing the allocations, or their covariance (i.e. which part would increase if another part decreases). In this paper the Dirichlet distribution is used to describe uncertain allocations because it naturally represents allocations that add up to 100%, and because it has a simple parameterisation in terms of the mean shares and a "concentration parameter" determining the level of uncertainty. We consider the following rules for the interpretation of a "10% uncertainty" relative to different "reference parts": (**a**) 8 percentage points (pp) on 80%, (**b**) 1.7 pp on 17%, (**c**) 0.3 pp on 3%.

Fig. 2 compares the results of these rules to the expected outcome – 10% variations in the size of the output parts. Unsurprisingly, the expected uncertainty range is observed for the reference part whose uncertainty was specified: **a** has the expected range for the first part, **b** for the second part, etc. But this example shows that parts smaller than the reference part have greater than expected uncertainty, while parts bigger than the reference part have smaller than expected uncertainty. Because bigger parts have a bigger influence on the overall results, it is better to exaggerate the uncertainty of small parts than it is to deny the uncertainty of large parts. We therefore use rule **a**: adjust the distribution to match the uncertainty in the largest part to the specified value. This approach is followed for both the allocation of Final energy to end-uses, and for the allocation from end-uses to conversion devices. A more formal explanation of the equations used is shown Section 3 of the Supporting Information.

3.2.1.3. Conversion efficiencies. Statistical offices at times provide average conversion efficiency estimates obtained using sales data or expert estimation. Since these estimates are rare, the method to derive national average efficiencies from publicly available data described in Section 3.1.4 is used for most devices.

Table 3
Pedigree matrix employed to assess the data quality of the national average energy efficiencies. The lower the score value the higher the quality of the data.

Indicator	Definition	Score: 1	Score: 2	Score: 3	Score: 4
Reliability	Focus on the data source: documentation of data generation, e.g., assessment of sampling method, verification methods, reviewing processes.	Methodology of efficiency data measurement is well documented and consistent, peer-reviewed data	Methodology of efficiency data generation is described, but not fully transparent; no verification	Methodology not comprehensively described, but principle of data generation is clear; no verification	Methodology of data generation unknown, no documentation available
Completeness	Composition data set is assessed. Possible over- or underestimation is assessed	Data includes all types of relevant conversion devices	Data includes main types of relevant conversion devices	Data includes partially main types of conversion devices. certainty of data gaps	Only fragmented data available; important conversion device types are missing
Temporal correlation	Congruence of the available data and the ideal date with respect to time reference	Value relates to the right time period	Deviation of value 1–5 years	Deviation of value 5–10 years	Deviation more than 10 years
Geographical correlation	Congruence of the available data and the ideal data with respect to geographical reference	Value relates to the studied region	Value relates to similar socioeconomical region (GDP, consumption pattern)	Socioeconomically slightly different region	Socioeconomically very different region
Other correlation	Congruence of the available data and the ideal data with respect to technology, product, etc.	Value relates to the same conversion device	Values relate to similar conversion device technology	Data deviates from conversion device of interest, but rough correlations can be established based on experience or data	Values deviate strongly from conversion device of interest, with correlations being vague and speculative

The uncertainty of the efficiency estimate is quantified using two parameters: the quality of the underlying data (which quantifies the magnitude of the uncertainty) and the quality of the central estimate (which determines the probability distribution is used).

Data quality is assessed in a consistent way using a pedigree matrix similar to the one used by Laner et al. [50] for Material Flow Analysis. The data is assessed using five qualitative indicators: Reliability, Completeness, Geographical Correlation, Temporal correlation, Other correlation. The score obtained by each data point is used to determine the magnitude of the uncertainty of each estimate. The definition of each indicator, as well as the qualitative aspect associated with each score are show in Table 3, while the values associated with each score are shown in Table 1 found in Section 2.1. of the Supporting information.

Since efficiency values are bound between zero and one, and because the range of efficiencies can be either small or large depending on the technology, the uncertainty is defined as a fraction of the efficiency range (R) for each technology as seen in Eq. (8).

$$\beta = R \sum_i s_i \tag{8}$$

where β is the uncertainty parameter for each efficiency, R is the performance range for a given technology, s is pedigree matrix score for that technology and the index i refers to each indicator.

Once the uncertainty (β) of the estimate is quantified, a probability density function is selected to represent the distribution of the uncertainty. The distribution is chosen according to the quality of the central estimate.

- *Uniform distribution*: if there is no information available to provide a central estimate of the average efficiency. The difference between the lower and upper bound of the distribution is equal to β.
- *Triangular distribution*: if there sufficient information to provide a central estimate of the efficiency. The expected value of the distribution is set to the central estimate; while difference between the upper and lower bound is β
- *Normal distribution*: If a reliable central estimate for the average efficiency is available. The expected value of the distribution is the central estimate, while the standard deviation is $\frac{\beta}{4}$.

3.2.2. Uncertainty propagation

The uncertainty is propagated through the model using a Monte Carlo simulation technique. The simulation is implemented using a Python and a MatLab script, using 5000 samples are drawn from each of the probability distributions and then multiplied together to obtain a sample of estimates for Useful energy. The value of 5000 was chosen to provide numerical stability to the resulting distributions without excessive computational effort.

3.3. UK data sources

In this section, the sources of data used to calculate the Useful energy consumption of the UK are described. The method followed is summarised in Fig. 3.

3.3.1. Energy balance

The 2013 Eurostat energy balance for the UK [66] is used for the analysis (the department for Business, Energy and Industrial Strategy (BEIS) does not publish a disaggregated balance). Data on the uncertainty associated with each of the fuels is retrieved from the 2016 GHG inventory report [67], while an explanation of the methodology use to compile the data is found in a 1998 Department for Environment, Food & Rural Affairs (DEFRA) report [62]. The uncertainty of liquid and gaseous biofuels is assumed to be the same as their fossil equivalents, since their reporting follows similar centralised practices [68]. Solid biomass consumption in the energy sector and industry is assumed to

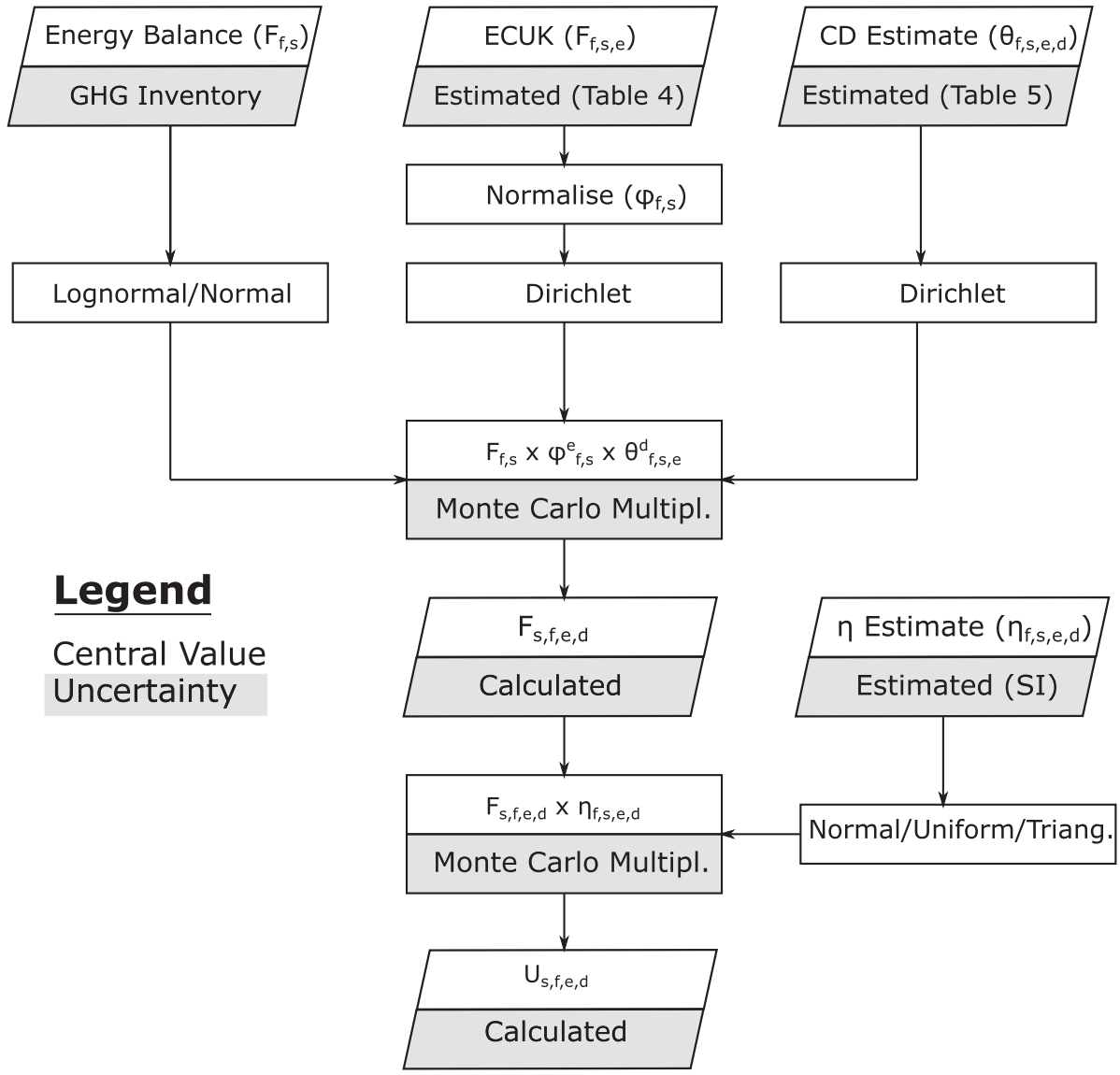

Fig. 3. Flowchart summarising the steps taken to calculate the Useful energy demand of the UK and its uncertainty, from data sources to results. The text shaded in grey refers to the uncertainty of the data, described in the transparent boxes. The text in brackets indicates where the assumptions are found in the text. The abbreviations used are the following. ECUK:Energy Consumption UK, CD: Conversion Device, SI: Supporting Information.

have the same uncertainty as coal, since it is reported by similar organisations. Solid biomass use in the residential sector is reported to have significant uncertainty and is therefore assigned an uncertainty of 50%.

3.3.2. End-use allocation

Information of the end-use allocation is retrieved from the Energy Consumption UK (ECUK) report [69]. Since not all end use categories reported in ECUK match those shown in Table 1, it is necessary to make some judgements on the split between different categories, adding additional uncertainty. For electricity use in the residential sector, data from the Household Electricity Survey [28] an empirical study of electricity use in British households is used due to its higher resolution and reliability. For the Agriculture, Fishing and Forestry (AFF) sector, no end-use consumption data is available on ECUK, therefore the allocation is based on a DEFRA study performed in 2007 on energy use in farms [70].

Table 4 summarises the uncertainty value associated with each end-use allocation used in this study. Residential sector end-use breakdown is based on the Cambridge Architectural Hosing Model [71], for which an uncertainty analysis has been performed. The service sector breakdown is based on the Building Energy Efficiency Survey [72] and its reliability has been compared with other well-established simulation models [73]. The industrial breakdown is based on the non-domestic Energy and Emissions Model, which uses a survey last conducted over 17 years ago [74].

Table 4
Summary of the uncertainty associated with each end-use allocation vector estimated by the author. Further details about the rationale underpinning the values is found in Section 1 of the Supporting Information.

Sector	Uncertainty (%)
Residential	18
Service and Commercial	20
Industrial	25
Agriculture, Forestry, and Fishing	25

3.3.3. Allocation to devices

For the majority of flows, only one device is associated with a given

Table 5
Combinations of sector, fuel and end-use which require further allocations to determine the share of energy used by a specific device. The Uncertainty column indicates the uncertainty associated with the allocation.

Sector	Fuel	End-use	Gas turbine (%)	Diesel engine (%)	Spark ignition engine (%)	Uncertainty (%)
Industry	Gas	Mechanical	75		25	20
Industry	Liquid fuel	Mechanical	30	60		20
Road	Liquid fuel	Mechanical		63	37	1.2
Aviation	Liquid fuel	Mechanical	99.50		0.50	5
Services	Liquid fuel	Mechanical		50	50	20

sector/fuel/end-use combination. For example, only the "Electric Heater" can deliver residential space heating using electricity. There are four instances, listed in Table 5, where further allocations are required. In all cases, the ambiguity arises because more than one type of internal combustion engine can be used to deliver mechanical energy from fossil fuels. The energy balance distinguishes between Diesel Fuel, Gasoline Fuel and Type A Jet fuel. This distinction is sufficient to make most of the required allocations. Liquid fuel used in Industry, is split between gas turbines and diesel engines according to the global sales of Diesels and Gas Turbines for mechanical Drive obtained from "Diesel and Gas Turbine Worldwide" [75]. Gas use in industry is assumed to be either used in spark ignition gas engines or gas turbines, with a strong predominance of the latter technology. Liquid fuel in the service sector is split equally among diesel and spark ignition.

3.3.4. Conversion efficiencies

Average values for the conversion efficiency of each device category in the UK in 2013 is sought. Data is sourced from both national and international databases and catalogues. Whenever possible, official governmental figures are used. A full description of the data and assumptions made can be found in Section 2.1 of the Supporting information.

4. Results

4.1. Useful energy balance

The energy flow through the UK, is modelled to obtain estimates of Useful energy consumption with the results shown in Table 7 as a Useful energy balance.

In Fig. 5 a Sankey diagram mapping UK energy flows from Final to Useful energy is shown. The Final energy consumption was 5.8 EJ y^{-1} (1 EJ = 10^{12} MJ) while a Useful energy consumption of 3.9 EJ y^{-1} was estimated. Hence the average conversion efficiency is of 67%. The largest Useful energy category is Heating, which accounts for 64% of total Useful energy consumption while Motion is the second most used form of Useful energy consumption, accounting for 22%. The transport sector is the one that consumes most Final energy (2.2 EJ) while the Residential sector consumes most Useful energy (1.6 EJ).

Fig. 4 shows the contributions of Final and Useful energy, by conversion devices, to sectors. The lower contribution of the transport sector in terms of Useful energy consumption is because mechanical energy enjoys the lowest conversion efficiencies compared to other Useful energy categories. Motion is provided with an average conversion efficiency of 34% while the same value for heating is 90%.

Table 6 shows the average conversion efficiencies for each sector and each end-use category. It can be observed that the provision of coolth has the highest efficiencies as well as the highest uncertainties. Uncertainties are higher for the delivery of Motion than for Heating. The data collected enables comparisons in the rate of change of average conversion device efficiencies against historical results [17]. For example, lighting efficiency has increased from 6% in 1978 to 10% in 2013, thanks to the development of new lighting technologies and their comparatively fast market penetration. Also the efficiency of space heat delivery has increased from 64% to 83%, mainly thanks to the substitution of oil and coal for natural gas and electricity. On the other hand, there seems to have been a very small increase average petrol engine efficiency and the average efficiency of electric motors has decreased. One possible reason for this trend is the increased market penetration of smaller, less efficient, motors in buildings.

4.2. Uncertainty analysis

The analysis shows that there is great variability in the uncertainty associated with energy statistics. Final energy statistics found on the energy balance have mostly low uncertainties (⩽5%) with the exception of Biomass and Waste for which there are higher uncertainties (around 30%). Fig. 4 show the magnitude and uncertainty of the Final energy consumption, and of the Useful energy output from each conversion device. Boilers, have the lowest uncertainty (around 7%) while the output of light devices has the highest (126%).

One clear trend is that smaller energy quantities are more uncertain than larger ones. For example in Industry, Useful energy for illumination has an uncertainty of 126% while Useful energy for heating has an uncertainty of 6%. Higher level of aggregation are also linked to lower uncertainty, therefore entire sector uncertainties are lower than those associated with a specific device.

The uncertainty generation is highest in the allocation of Final energy to end-uses. The uncertainty associated with Final energy consumption in a sector for each fuel varies between 0.5 % and 55% with a median uncertainty of 5%. While the uncertainty associated with Final energy consumed for each end-use in each sector ranges between 1.5% and 120% with a median uncertainty of 34%. Similar uncertainties are observed for Useful energy estimates broken down by sector and end-use, with only a slightly higher median uncertainty.

It is important to note that the results of this uncertainty analysis are as valid as the assumptions outlined in the methodology section and do not include the "modelling" uncertainty which is associated with the assumptions made. However, the analysis has aimed to be conservative throughout, to avoid being overconfident about the uncertainty of the results.

5. Discussion

This study provides a methodology to quantitatively assess the uncertainty associated with Useful energy estimates for the first time. The Useful energy balance of the United Kingdom in 2013 was calculated and its uncertainty quantified.

5.1. Useful energy balance

The differences between the Final and Useful energy balances are similar to those observed in previous studies of the UK in national [38], European [40], and global studies [22]. There are two main considerations shown by the analysis. First, the provision of Mechanical energy has the highest improvement potential in terms of Final to Useful efficiency. A policy that could help bridge this gap is weight-based fuel economy standard which compels manufacturers to improve the efficiency of internal combustion engines using available technologies such as cylinder deactivation or Atkinson cycle engines [76].

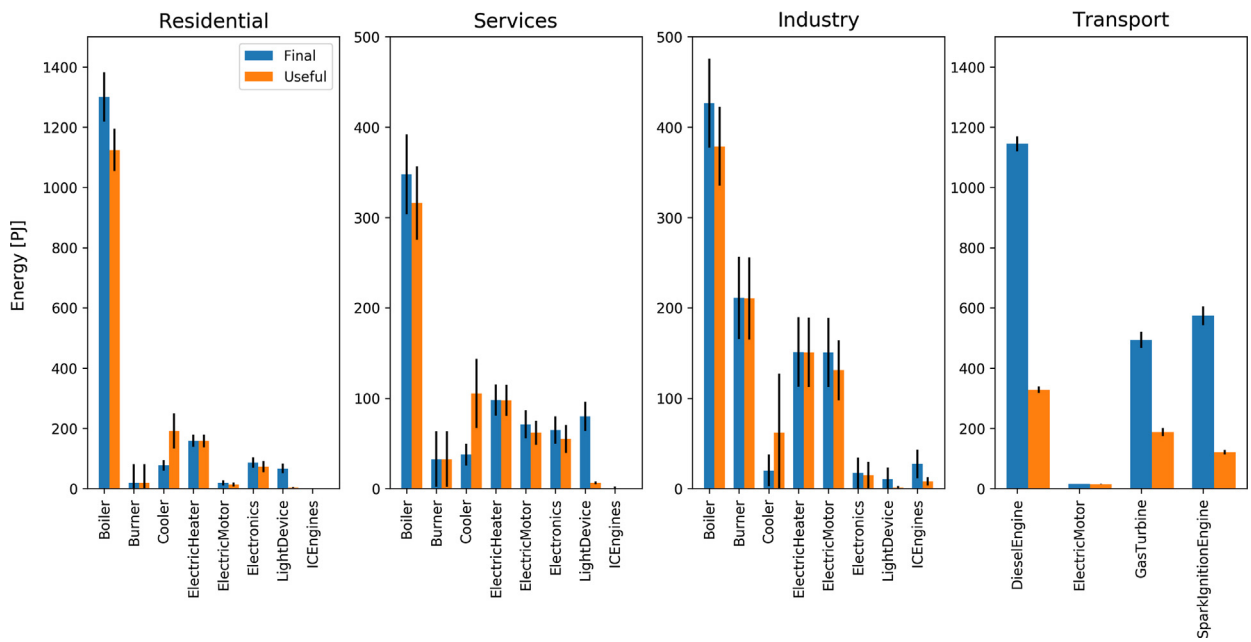

Fig. 4. Final and Useful energy consumed and produced by each end-use conversion device in each sector. The error bars indicate the range of two standard deviations. Useful energy bars are lower than Final energy bars because of conversion losses (except for cooling, where efficiencies ⩾1 are observed). The magnitude of the error bars shows that there is not always enough information to rank end-use consumption because the uncertainty is larger than the differences between estimated consumption figures.

Second, the industrial sector is the most efficient sector because it tends to use the largest (and thus most efficient devices) and relies more than any other sector on direct combustion, which has a 100% first law efficiency. While Primary energy consumption lies outside the boundaries of this analysis, it is important to note that the relative Primary to Useful efficiency is different from the Final to Useful efficiency trends outlined here. For example, while electric motors display a very high Final to Useful efficiency, their Primary to Final efficiency can be on par with the one of Diesel engines (further details can be found in Cullen et al. [42]).

The energy conversion efficiency values used in this analysis of UK energy flows, have been revised based on the latest efficiency data from tested conversion devices. This update was long due in the literature and it enables the assessment of some long term trends by comparing the results with values used by Eurostat in the 1970s [17]. As seen in Table 6, there is considerable variation in the uncertainty associated with efficiency: showing efficiency values with a confidence interval should be standard practice, and any claim of year on year variation should at least be checked for statistical significance.

From the conversion efficiency data collection procedure, it was

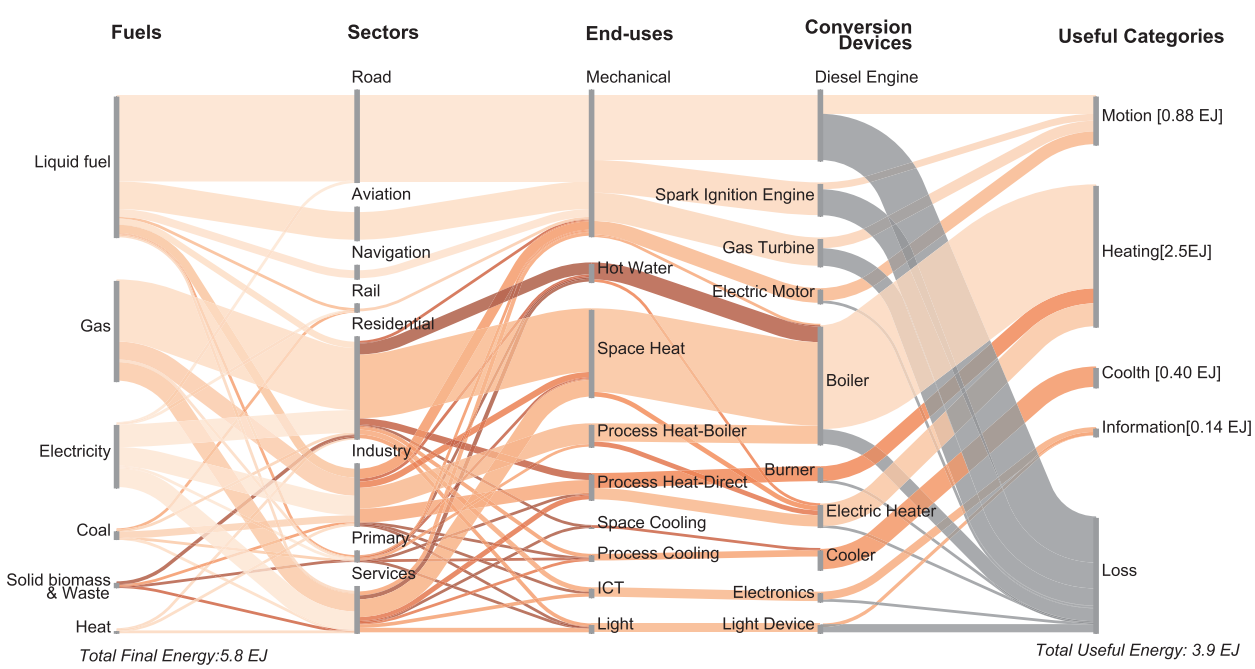

Fig. 5. Sankey diagram representing the energy data used in this study. The width of the lines represents the quantity of energy (in PJ, where 1 PJ = 10^9 MJ) while the intensity of the colour represents the uncertainty (in %) of each flow. The first four layers are loss-less because they show only allocations, losses are only incurred in the stage between conversion devices and Useful energy categories.

Table 6
Average conversion efficiencies from Final to Useful Energy for each sector, aggregated by Useful energy category.

	Coolth	Heating	Illumination	Information	Motion
Industry	309% ± 347%	94.2% ± 1%	13% ± 2%	85% ± 27%	83.8% ± 3%
AFF	311% ± 345%	89.2% ± 1%	13% ± 2%		60.5% ± 3%
Residential	248% ± 104%	88.3% ± 1%	6% ± 2%	84.8% ± 26%	74% ± 5%
Services	289% ± 77%	93.6% ± 3%	8% ± 2%	84.9% ± 26%	86.9% ± 3%
Aviation					38% ± 3%
Navigation					39% ± 3%
Rail					72.7% ± 3%
Road					25.1% ± 1%

observed that device efficiencies do not show large year on year variations but they do change over longer time periods, albeit with different rates. Devices with short lifetimes and fast technological progress (e.g. light bulbs) must be updated with higher frequencies compared to devices that have long lifetimes and slower technological progress (i.e. industrial boilers or jet engines).

The present study is a snapshot view of the Useful energy balance of the UK because the focus of the study was on the development an uncertainty quantification framework. It is recognised, that the full benefit of Useful energy accounting are found in consistent time series and in comparisons between countries. Future work should employ the framework provided here to build consistent international accounts of Useful energy (such as done by De Stercke et al. [22]) while also providing a quantification of the uncertainty associated with the data. It is hoped that such a database could help stimulate further research in Useful energy accounting and help bridge the gap between supply side and end-use side energy statistics.

5.2. Uncertainty analysis

The results from the uncertainty analysis show three broad trends. First, end-use application with smaller shares of energy have higher uncertainty. This results from the nature of the distribution used to model the uncertainty of the allocation vector, and because at parity of absolute uncertainty, smaller shares will have higher relative uncertainties. Second, results with a higher level of aggregation have lower uncertainty, because the uncertainties are assumed to be uncorrelated they cancel to some extent in the aggregated value, thus reflecting the intuition that we are more confident about aggregated values than detailed breakdowns of data. Third, the main source of uncertainty is found in the allocation to end-use applications. It was previously thought that both end-use allocation and efficiency values contributed to the uncertainty of Useful energy estimates, however this study has shown that the key element that results in uncertainty is the allocation to end-use applications. One of the reasons for the higher uncertainty of the allocation to end-uses is the fact that practitioners are reluctant to quantify uncertainty while compiling national level statistics and thus only very conservative assumptions can be made about these values.

The interpretation of the uncertainty results is facilitated by defining an acceptability threshold, and conveniently statistical offices often define a range of acceptable uncertainty for national surveys. For example, the UK's Annual Survey of Hours and Earnings considers acceptable uncertainty values between 20% and 40% [77] (they use the Coefficient of Variation metric, which is half the uncertainty as defined in Eq. (6)). In a study by Eurostat, examples of acceptability thresholds for uncertainty were found between 10% and 33% [78], while the American Community Survey, considers values with uncertainties up to 24% as "reliable" [79]. Using these examples as guidelines, Useful energy estimates with uncertainties below 25% are deemed sufficiently reliable. Table 7 shows that Useful energy estimates for the provision of Heating in all sectors (with the exception of Heating from biomass) and of Mechanical energy in the Transport sector are sufficiently reliable; these sectors account for 85% of total Useful energy consumption. All other Useful energy categories are too uncertain to be deemed acceptable. Therefore, although the uncertainty of Useful energy estimates is higher than Final energy statistics, this study shows that most Useful energy estimates are reliable, and statistical offices only need to focus on reducing the uncertainty in a small number of Useful energy categories.

In the specific case of the UK, an improvement of the industrial end-use energy statistics would have the greatest impact on the reliability of Useful energy accounting with the smallest effort. This could be achieved by an energy end-use application survey for the Industrial sector. A possible practical solution would be to adopt the survey methodology used for the US Manufacturing Energy Consumption Survey [31], where the energy managers of a sample of industrial facilities report on the end-use applications of their energy consumption.

At a global level, the advent of the *Smart Grid* vision in buildings, and of the *Internet of Things* paradigm in the manufacturing sector are likely to increase the quantity and quality of metered end-use consumption data for energy statistics. In particular, new development in metering and sensing technology, such as the Non Intrusive Appliance Load Monitoring [80], smart plugs [81], and natural gas sensors [82] enable consumers to be aware of their energy consumption. The decreasing costs of sensing and data processing technology (which are at the basis of the Industry 4.0 revolution [83]) mean that an increasing share of energy consumption will be monitored. These new developments mean that increasing quantities of data on the end-uses of energy will become available in the near future. It is recommended that statistical offices make use of these new tools for their data collection protocols as this would bridge the gap between the reliability of supply and demand side statistics. This is expected to facilitate the deployment of more detailed policies on the end-uses of energy and thus reduce the imbalance between supply and demand side policy action.

Three avenues for further research are highlighted by the results of this analysis.

- Further research is required to improve the accuracy of the uncertainty estimates for allocating energy. There are at least two ways to improve the robustness of the data used to assess the uncertainty of end-use energy statistics. Firstly, one could employ expert elicitation techniques to canvas a number of practitioners to extract probability density functions to be associated to the various parameters. Secondly, the uncertainty analysis could be performed directly on the models that are used by statistical offices to estimate the end-use energy consumption in each sector.
- The uncertainty analysis should also be expanded to include Primary energy statistics, while at the moment there is no available technique to estimate their uncertainty. It would be desirable for all users of energy statistics to if an assessment of the quality of such numbers was made available by statistical agencies or if a suitable probabilistic model could be employed to infer their uncertainty.
- A comparative study of the techniques used to estimate energy end-uses could shed light on the international best practices which could be emulated in other countries to improve the quality of end-use

Table 7
Useful energy balance [PJ] for the UK in 2013. Values are expressed for each sector and energy carrier combination and contain an uncertainty estimate.

Sector	Energy Carrier	Cool (%)	Heat (%)	Illumination (%)	Information (%)	Motion (%)
AFF	Coal		0.2 ± 11			
	Electricity	6.7 ± 79	3.9 ± 37	0.2 ± 69		5.6 ± 25
	Gas		39 ± 4			
	Liquid fuel		5.6 ± 76			6.9 ± 35
	S. Bio. & Waste		5.5 ± 57			
	Total	6.7 ± 79	54 ± 10	0.19 ± 69	0 ± 0	12 ± 22
Industry	Coal		119 ± 8			
	Electricity	61.9 ± 105	151 ± 25	1.3 ± 126	15 ± 98	131 ± 25
	Gas		281 ± 7			5.2 ± 111
	Heat		30.8 ± 6			
	Liquid fuel		139 ± 11			2.6 ± 108
	S. Bio. & Waste		19.4 ± 26			
	Total	61 ± 105	739 ± 6	1.33 ± 126	14 ± 98	138 ± 24
Residential	Coal		24.6 ± 7			
	Electricity	191 ± 31	158 ± 13	4 ± 28	73.6 ± 26	14 ± 48
	Gas		971 ± 4			
	Heat		2.2 ± 5			
	Liquid fuel		98 ± 3			
	S. Bio. & Waste		47.8 ± 59			
	Total	191 ± 31	1302 ± 4	4.0 ± 28	73.6 ± 26	14 ± 48
Services	Coal		0.7 ± 5			
	Electricity	105.2 ± 36	97.8 ± 18	6.4 ± 23	55.1 ± 28	61.9 ± 22
	Gas		305 ± 11			
	Heat		16.7 ± 5			
	Liquid fuel	0.1 ± 415	24 ± 6			0.1 ± 209
	S. Bio. & Waste		1.9 ± 48			
	Total	105 ± 36	446 ± 8	6.4 ± 23	55 ± 28	62 ± 22
Aviation	Liquid fuel					188 ± 6
Navigation	Liquid fuel					55.2 ± 4
Rail	Electricity					14.9 ± 2
	Liquid fuel					9.5 ± 16
Road	Electricity					0.1 ± 6
	Liquid fuel					384 ± 3

energy statistics.

5.3. Conclusion

This study is the first attempt to rigorously quantify the uncertainty that is associated with Final and Useful energy balances–which are extensively used in national level energy system modelling. This study provides three main contributions to the wider energy studies literature. First, a novel methodology is developed to enable the quantification and assessment of the uncertainty associated with Final and Useful energy statistics using a Bayesian framework. Second, new data on the efficiency of ten end-use conversion devices is compiled and it is used to estimate their average efficiency. Third, the Useful energy balance of the United Kingdom is estimated with updated data.

The new efficiency data suggests that it is important to collect up to date country specific efficiency data and that year-on-year variations are small but vary for different end-use technologies. The uncertainty analysis shows that the largest source of uncertainty is the allocation to energy end-uses where the uncertainty of the energy flows goes from a median value of 5% to one of 34%. The transport sector results are the most certain while, and the provision of Useful Heating is the most certain Useful category. Overall, 85% of Useful energy consumption has uncertainties below the acceptability threshold of 25%. While the estimates obtained are more unreliable than traditional Final energy statistics, it is believed that a relatively small improvement in the end-use data quality could turn Useful energy into a viable energy indicator for policy design and evaluation. The advent of cheaper and widespread sensing equipment and data processing technology will bring about more information about the end-uses of energy. Statistical offices are advised to make use of this new information to improve data collection protocols and thus improve the reliability of end-use energy statistics.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.apenergy.2018.06.063.

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