Energy performance of buildings: A quantitative approach to marry calculated demand and measured consumption

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Abstract

Energy Performance Certificates (EPCs) for residential buildings are supposed to inform about the efficiency of heating and domestic hot water preparation in buildings under standardised boundary conditions regarding user behaviour and climate parameters. In a way EPCs represent a virtual test rig for the building to demonstrate whether it complies with the requirements of the corresponding energy savings ordinance.

Measured consumption usually differs from the calculated demand in a typical manner, in particular when, as in EPCs, simplified calculation models and standard specifications are applied: For existing, not yet modernised buildings it tends to be lower, for refurbished or new buildings higher than calculated. Partly this can be attributed to what is called prebound or rebound effects[1]. Of course this deviation is not desirable since calculated energy saving and cost effectiveness of refurbishment measures are over-estimated. A layperson does not really understand the difference in numbers between EPC and energy bill, f.i.

These effects were analysed in two projects. The first one referred to the Energy Performance Certificate Register for residential buildings in Luxemburg, run by the Luxemburg Ministry of the Economy, containing 20,000 records, each consisting of 174 parameters per building, including the measured consumption[2]. The second one analysed 92 well-documented records of non-residential buildings in Germany consisting of hundreds of building parameters including measured consumption. The latter had been gathered in the research project "Teilenergiekennwerte von Nichtwohngebäuden" (TEK)[3] financed by the German Federal Ministry of Economic Affairs and Energy.

Statistical methods such as multiple linear regression and error calculus were applied to study the gap between measurement and calculation in detail. This opens a quantitative approach to calibrate calculated demands by measured consumptions and thus quantify the inevitable uncertainties of EPCs.

Introduction

During the heating period, buildings in temperate latitudes like in Central Europe need a permanent supply of heating energy in order to maintain comfortable room temperatures. The gradient of room to ambient temperature is the driving factor for thermal heat flow through the building envelope. These processes of heat transfer are theoretically well understood. Various validated simulation tools are at hand.

1.Minna Sunikka-Blank, Ray Galvin (2012): Introducing the prebound effect: the gap between performance and actual energy consumption, Building Research & Information, 40:3, p. 260–273.

2. Markus Lichtmeß (2012): Forschungsprojekt Gebäudedatenbank und Plausibilitätscheck im LuxEeB-Tool, interne Ergebnisse, Goblet Lavandier & Associés Luxemburg.

3. Michael Hörner et al. (2014): Teilenergiekennwerte – Neue Wege in der Energieanalyse von Nichtwohngebäuden im Bestand, IWU 05/14, ISBN 978-3-941140-38-7.

For existing buildings, in particular when it comes to a great number of them or a whole building stock, values of these input variables usually are not known with the accuracy and the time step widths necessary, in particular regarding parameters of user behaviour. Thus, even the most elaborate simulation tools will only calculate the energy performance of buildings as accurate as the input variables allow for.

The best thing to do then is to analyse how uncertainties of the input variables propagate to uncertainties of the results. For our purposes the specific delivered energy demand q_D of a building may be considered as a function of independent input variables such as U-values U_i and areas A_i of i different parts of the envelope, expenditure factors e_j of j heat generators and distributions, k parameters of user behaviour B_k, such as room temperatures, and l climate parameters C_l, e.g. the ambient temperature.

$$q_{f,D} = q_{f,D}\left(U_i, A_i, e_j, B_k, C_l\right) \quad (1)$$

When it comes to issue an EPC, however, the objective is to calculate the energy demand of the building q_D^{EPC} with reasonable effort in a standardised setting in order to compare it to other buildings and to certify that legal requirements of the energy savings ordinance are met. Simplified calculation schemes are applied and of course compliance must be certified assuming standard specifications of user behaviour B_k^{std} and climate parameters C_l^{std}. Measured energy consumption of the building q_C does not comply with this requirement, since it reflects individual user behaviour and actual climate conditions quite often deviating considerably from standard specifications. The demand calculated according to EPC specifications may then be considered as a special subclass of function (1) with standardized boundary conditions

$$q_{f,D}^{EPC} = q_{f,D}^{EPC}\left(U_i, A_i, e_j, B_k^{std}, C_l^{std}\right) \quad (2)$$

As already mentioned, for existing buildings many of the physical input variables of the building envelope and the heating plant are not known exactly. In a certification scheme, conservative assumptions have to be made then. Additionally empirical data on user behaviour show clearly that occupants of older not yet modernised buildings do use energy more consciously and f.i. set room temperatures in a way that the average temperatures in buildings result significantly lower than specified in standards[4], fuel costs assumably being a strong economic incentive. These conservative assumptions of heat losses together with deviations from the standards of user behaviour lead to the well-known effect: Specific values of calculated energy demands in EPCs tend to considerably overestimate specific values of measured energy consumption, at least for non-refurbished existing buildings. There is some evidence that in very energy-efficient buildings with specific values of energy demand below 50 kWh/m²a this effect is reversed[5].

In energy consulting, on the other hand, most often similar calculation tools are used as in EPCs and it is good practice to calibrate results from demand calculations to measurements in order to calculate savings potentials reliably. This requires realistic assumptions of user behaviour and adjustment of physical building parameters within their usual ranges of uncertainty, often times measured on site. Thus, calculation models in EPCs, even though simplified, are not intrinsically flawed, but in many cases standard specifications do not and are not supposed to match actual building specifications. Consumers are not always well aware of these differences.

Problems arise when calculated demands from simplified calculation schemes with standard specifications are used to assess savings potentials, which are regarded as realistically achievable. A calculation method that includes presumable changes in user behaviour in the future, after refurbishment, is required then, with combined approaches based on standard calculations as well as measured consumptions[6] having been proposed earlier.

Fortunately, data stock on energy performance of buildings has increased considerably in the last years. Thus, we suggest more elaborate calibration procedures based on sound statistical analysis of this data stock and the propagation of uncertainties of independent variables on the uncertainty of a function based on them. These are well-known problems in the empirical sciences.

In the first part of this paper we apply methods of multiple linear regression to analyse sets of variables ($q_{f,C,i}$, $q_{f,D,i}^{EPC}$, $X_{1,i}$, … , $X_{m,i}$) relating values of measured delivered energy consumption $q_{f,C,i}$ as the dependent variable to values of calculated delivered energy demand $q_{f,D,i}^{EPC}$ as well as various other independent variables $X_{m,i}$ of N residential buildings i = 1 … N in the Luxemburg EPC Register. Gaussian error calculus is then applied to estimate the uncertainty in energy demand calculations $u(q_D)$ propagated from the uncertainties of the parameters of user behaviour $u(B_k)$: $u(q_D) = f(u(B_1), \dots, u(B_k))$. The benefit for regression analysis is discussed.

In the second part we undertake regression analyses of 92 non-residential building records in the TEK-Database and derive calibration factors for demand calculations with the TEK-Tool[7] to be used in energy consultancy and scenario calculations in the German building stock.

Statistical Analysis of Energy Performance Certificates for residential Buildings in Luxemburg

THE LUXEMBURG ENERGY PERFORMANCE CERTIFICATES REGISTER

The EPC in Luxemburg defines a threefold labeling scheme for new and existing residential buildings with regard to energy need for heating, primary energy demand and CO_2-emissions. Besides the certification, that legal requirements are met, its objective is to give reliable information on the energy standard of

4.Franz Schröder et al. (2014): Reale Trends des spezifischen Energieverbrauchs und repräsentativer Wohnraumtemperierung bei steigendem Modernisierungsgrad im Wohnungsbestand, Bauphysik 36 (2014), Heft 6, p. 309–324.

5.Alicia Graf (2016): Analyse des Energieverbrauchs wärmetechnisch modernisierter Mehrfamilienhäuser – Entwicklung von Verbrauchsbenchmarks zur Beurteilung der Energieeffizienz, Masterthesis Institut für Massivbau, Technische Universität Darmstadt, 2016, S. 38–43.

6.Manfred Casties (1997): Untersuchung zum Zusammenhang zwischen Nutzerverhalten und Heizenergieverbrauch, -bedarf von Wohngebäuden; Verlag für Wissenschaft und Forschung, Berlin 1997.

7.Michael Hörner, Jens Knissel et. al. (2014): Berechnungsgrundlagen des TEK-Tools Version TEK 6.2, IWU 03/14, Darmstadt 2014, ISBN 978-3-941140-36-3 (TEK-Tool (V 6.3-DB4.34), downloadable at http://www.iwu.de/forschung/energie/laufend/teilenergiekennwerte-von-nicht-wohngebaeuden/).

buildings f.i.in sales ads. Only approved experts are eligible to issue EPCs. The EPC Luxemburg[8] is based on a simplified demand calculation model with standardised parameters of user behaviour and climate. Remarkable is the fact, that for each existing building i in addition to the calculated delivered energy demand $q_{f,D,i}$ the measured consumption $q_{f,C,i}$ has to be indicated as soon as an EPC is issued, for new buildings four years after the beginning of operation. However, data of actual user behaviour and climate at the building site are not recorded in the database.

In 2014 the Luxemburg EPC Register was launched. EPCs issued after that date have to be registered. Since then a database of some 20.000 EPCs records has grown, each one consisting of 174 parameters. The EPC Register increasingly provides for an overview of the energy standard in the Luxemburg building stock and supports statistical analysis.

For the statistical analysis here only anonymised records of existing buildings were taken into account, for which calculated demand as well as measured consumption for heating and domestic hot water were available. A comprehensive quality control of EPCs has not yet been established; in particular concerning measured consumption, where not even weather correction can be assured. Plausibility checks have been built into the EPC software tool, so that grossly deficient or incomplete EPCs could be sorted out beforehand. Thus 4.407 EPC records of residential buildings in Luxemburg were selected from the Luxemburg EPC Register for the statistical analysis.

MULTIPLE LINEAR REGRESSION ANALYSIS OF CALCULATED DEMAND AND MEASURED CONSUMPTION

The graphical representation in Figure 1 of all pairs of values ($q_{f,C,i}$, $q_{f,D,i}^{EPC}$) of the 4.407 EPCs selected from Luxemburg EPC Register shows a well-known pattern then, that has been discussed in the corresponding literature [9, 10, 11]. With a perfectly realistic calculation scheme one would expect the data points to line up along the bisecting line. Instead we see a heavily dispersed data point cloud tilted towards the abscissa. The regression line is much less inclined than the bisect and the ordinate intercept is implausibly high.

As mentioned above problems arise when a savings potential is supposed to be calculated, f.i. for a mean building of this sample represented by the regression line in Figure 1, then a saving in calculated demand

$\Delta q_{f,D,i} = 200$ kWh/m²a as of Equation (5) corresponds to much less saving in estimated consumption

$$\Delta \hat{q}_{f,C,i} = 200 \times 0{,}28 = 56 \text{ kWh/m}^2\text{a}.$$

Some notions in regression analysis

For the sake of the analysis here we suppose that measured delivered energy consumption of buildings $q_{f,C}$ is a function of many influencing factors such as physical building properties, user behaviour and climate factors, many of which are well represented in a standardised demand calculation like the EPC, $q_{f,D}^{EPC}$, and other independent variables X_m, are to be identified yet

$$q_{f,C} = q_{f,C}\left(q_{f,D}^{EPC}, X_1, \ldots, X_m\right) \tag{3}$$

However, the exact function (3) is unknown. At least we can guess from Figure 1 that $q_{f,C}$ is directly proportional to $q_{f,D}$ and from physical reasoning of cause and effect we expect a linear dependence. Thus, we model $q_{f,C}$ to be a linear function of $q_{f,D}$.

$$q_{f,C}\left(q_{f,D}^{EPC}, X_1, \ldots, X_m\right) = b_0 + b_1 \cdot q_{f,D}^{EPC} + u \tag{4}$$

plus a disturbance quantity u, which accounts for all influences of user behaviour, uncertainties of measurement and the calculation model so far unknown. Since the coefficients b_k are unknown, equation (4) cannot be solved.

Based on the sample of 4.407 out of a principally infinite population of pairs of values we estimate a linear function

$$\hat{q}_{f,C} = \beta_0 + \beta_1 \cdot q_{f,D}^{EPC} \;, \beta_0 \approx 92, \beta_1 \approx 0{,}28 \tag{5}$$

with regression coefficients β_k being estimates of the unknown coefficients b_k. This leaves the difference between the measured consumption and its estimate, called residue,

$$\left| q_{f,C,i} - \hat{q}_{f,C,i} \right| = \hat{u}_i \tag{6}$$

representing the amount that cannot be explained by the function $\hat{q}_{f,C}$ alone. The regression coefficients β_k are most commonly determined by the Method of least Squares[12], minimizing the sum of squares of all residues of the sample.

For any residential building, with the calculated demand $q_{f,D,i}^{EPC}$ given, equation (5) then renders the best possible estimation $\hat{q}_{f,C,i}$ of the so far unknown "true" consumption $q_{f,C,i}$. The reliability of this prediction may be assessed by various tests.

Testing the Fit

Certain tests for the quality of a fit are usually applied[12]. For our purposes the standard error $\sigma(\hat{q}_{f,C,i})$ is of particular importance, since it is a measure for the standard deviation of the estimated consumption, corresponding to the dispersion of the estimators of different samples about the "true" consumption. Unfortunately the latter is not known until it has been measured. However, the standard error can be estimated $\hat{\sigma}(\hat{q}_{f,C,i})$ meaning that: With a probability of 68 % the "true" but unknown consumption $q_{f,C,i}$ will be in the interval $\hat{q}_{f,C,i} \pm \hat{\sigma}(\hat{q}_{f,C,i})$.

Most common is the Coefficient of Determination R^2, giving the ratio of the spread explained by the regression model and the total dispersion of the sample. In Figure 1 an R^2=31 % turns out. The p-value-test tells whether a variable is statistically significant. The F-test assesses the significance of the whole regression model.

8. Le gouvernement du grand-duché de Luxembourg (2007): Règlement grand-ducal du 30 novembre 2007 concernant la performance énergétique des bâtiments d'habitation (14.12.2007). Luxembourg : Service central de legislation.

9. Hans Erhorn (2007): Bedarf – Verbrauch: Ein Reizthema ohne Ende oder die Chance für sachliche Energieberatung?, Fraunhofer-Institut für Bauphysik, Stuttgart (available at: http://www.buildup.eu/sites/default/files/Manuskript_Messe_Bau_2007_Erhorn_Bedarf-Verbrauch_15_01_07_p.pdf).

10. Jens Knissel et al. (2006): Vereinfachte Ermittlung von Primärenergiekennwerten – zur Bewertung der wärmetechnischen Beschaffenheit in ökologischen Mietspiegeln, IWU, Darmstadt 2006 (available at http://www.iwu.de/fileadmin/user_upload/dateien/energie/werkzeuge/ Vereinfachte_Ermittlung_von_Primaerenergiekenwerten-1.0.pdf).

11. Edelgard Gruber et al. (2005): Energiepass für Gebäude – Evaluation des Feldversuchs. Schlussbericht an die Deutsche Energie-Agentur, Karlsruhe 2005.

12. K. Backhaus, K. et al. (2005): Multivariate Analysemethoden – Eine anwendungsorientierte Einführung, Springer-Verlag, Berlin 2005, 11. Auflage.

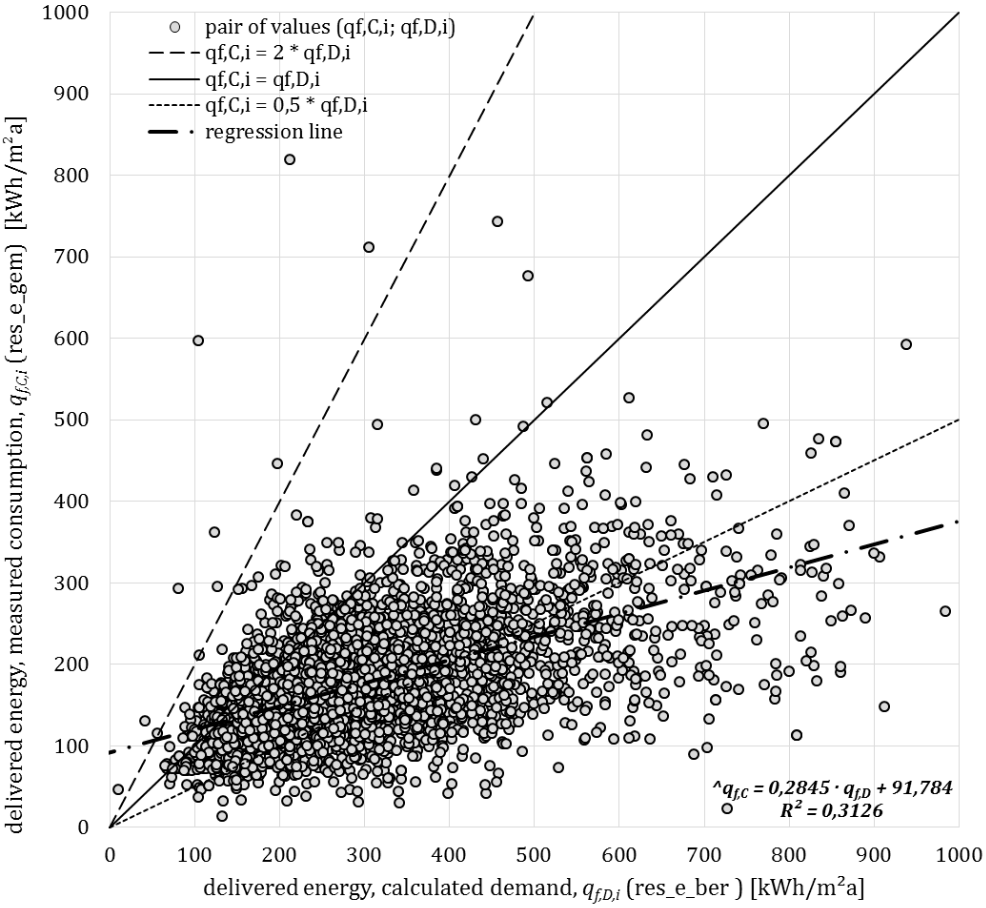

Figure 1. Measured energy consumption (heating and domestic hot water) plotted against calculated demand with standardized specifications of the 4.407 EPCs selected from Luxemburg EPC Register. Data Source: Luxemburg EPC Register, Luxemburg Ministry of the Economy, IWU (reg2_DB6_LN).

A special feature of the distribution in Figure 1 is heteroscedasticity, as the results of a Goldfeld-Quandt-Test[13] suggest. That means the spread in residues correlates to the calculated demand. This breaches one of the premises of linear regression and renders an estimation of the standard error which is too large for low demands and very small for high demands. This deficiency of the data can be accounted for by a non-linear, mostly logarithmic, transformation as shown in Equation (7) below.

Hypotheses

Hypotheses regarding further variables in the EPC Register were tested with regard to whether they could contribute to explain the still tremendous spread in the sample. As mentioned before, actual values of the parameters of user behaviour are not documented, building geometry and physical properties of building components and the technical plant are accounted for within the demand calculation. Thus only variables remain, that are not well considered in the whole spread of their occurrence by the simplified calculation model of the EPC. The following variables turn out to be significant: Number of dwelling units n_{DU}, reference area A_n, air tightness n_{50} and compactness A/V_e.

Luxemburg EPC

The requirement to indicate measured consumption in addition to the calculated demand in the Luxemburg EPC of course turned public awareness to the fact that often times there is a considerable delta between these two quantities. An empirically well based estimation function would allow for the prediction of a presumable consumption and its standard error in the EPC pointing out to building users that individual user behaviour may cause a considerable deviation of the actual consumption from the calculated demand.

Several regression functions were tested and analyses conducted. Keeping in mind that a certain arbitrariness is allowed, the final regression function for the Luxemburg EPC was defined as

$$Ln(\hat{q}_{f,C}) = \beta_0 + \beta_1 \cdot Ln(q_{f,D}^{EPC}) + \beta_2 \cdot n_{DU} + \beta_3 \cdot A_n + \beta_4 \cdot n_{50} + \beta_5 \cdot A/V_e \qquad (7)$$

13. Goldfeld-Quandt-Test compares sample-variances s^2 of two subsamples, f.i. s^2_{low} of the lower and s^2_{up} of the upper half of the observations. If $s^2_{low}/s^2_{up} > F_{crit}$, a critical value of the F-distibution, then a sample is considered heteroscedastic.

Table 1. Left: Values of the regression coefficients. Right: Regression statistics and analysis of variance.

Coefficient	Variable	Value
β_0	Intersect	2,427378825
β_1	$\mathrm{Ln}(q_{f,D}^{EPC})$	0,473667306
β_2	n_{DU}	0,029001539
β_3	A_n	-0,000343169
β_4	n_{50}	-0,014787772
β_5	A/V_e	0,164350872

Data Source: IWU (reg2_DB6_LN).

Regression Statistics	
Multiple Correlation-Coefficient	0.59
Coefficient of Determination	34 %
Adjusted Coefficient of Determination	34 %
Standard error	32 %
Observations	4,407
ANOVA	
F-test	458
F_{crit}	0

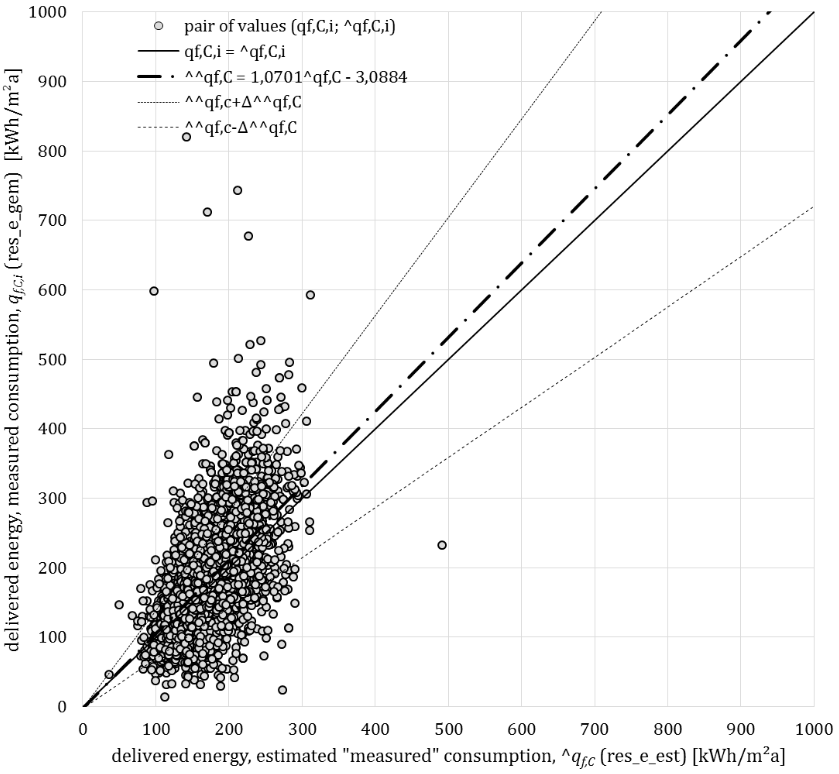

Figure 2. Measured energy consumption (heating and domestic hot water) plotted against estimated "measured" consumption of the 4.407 EPCs selected from Luxemburg EPC Register. The "regression" straight line ^^$q_{f,C}$ is shown only to illustrate the effect on an average building of the sample. Data Source: Luxemburg EPC Register, Luxemburg Ministry of the Economy, IWU (reg2_DB6_LN).

rendering the estimation function

$$\hat{q}_{f,C} = \left(q_{f,D}^{EPC}\right)^{\beta_1} \cdot e^{\beta_0+\beta_2 \cdot n_{DU}+\beta_3 \cdot A_n+\beta_4 \cdot n_{50}+\beta_5 \cdot A/V_e} \quad (8)$$

to determine the estimated "measured" consumption with regression coefficients and regression statistic as in Table 1. Defying immediate perception the coefficients may be interpreted as generalized slopes of a hyperplane in a 5-dimensional space, β_1 meaning that with $q_{f,D}^{EPC}$ increasing by 1 % $\hat{q}_{f,C}$ is doing so by β_1% whereas the other β_i mean that with the corresponding variable increasing by 1 unit $\hat{q}_{f,C}$ is doing so by β_i 100 %.

There are some interesting properties to this estimation function. While the logarithms in Equation (7) are to heal heteroscedasticity, the estimation function meets the origin and the standard error turns into a percental quantity. Correlation between the variables is reasonable and the F-Test indicates a statistically well confirmed regression model.

Based on this analysis, the Luxemburg EPC has been supplemented: From last year on the EPC depicts the estimate $\hat{q}_{f,C,i} \pm \hat{\sigma}(\hat{q}_{f,C,i})$ besides the calculated demand and, if already available, measured consumption, indicating to the owner of the building that from calculations with standard specifications only limited accuracy can be expected. The correct interpretation is: **With a probability of 68 % the true measured consumption will be in the range of the estimate's uncertainty.**

Figure 2 illustrates how this estimate relates to measured consumption in the sample. Still the cloud is quite spread out and there are extreme outliers. Further analysis is needed.

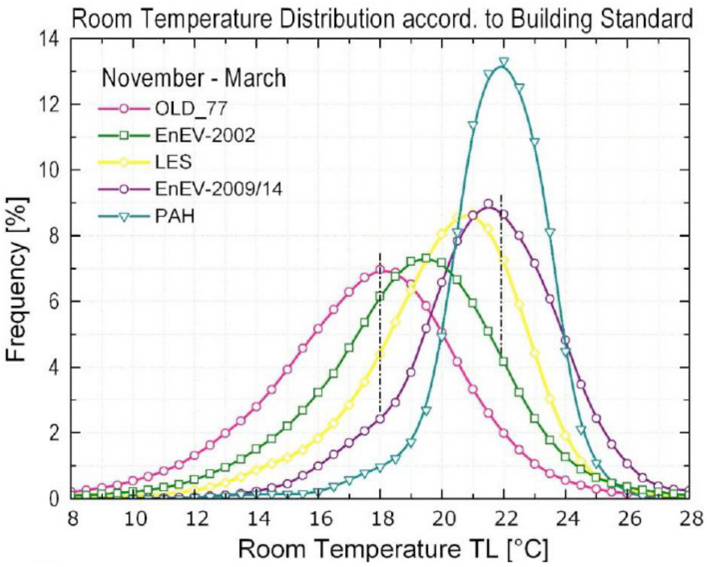

Figure 3. Frequency distributions of winter room temperatures within German rental flats, developing (from left to right) with advancing energy efficiency standards form buildings built prior to 1978 to passive houses. 4K integral increases of mean and median temperatures are evident. Data Source: METRONA (2017).

ESTIMATION OF THE INFLUENCE OF USER BEHAVIOUR ON CALCULATED ENERGY DEMANDS

As pointed out before the actual user behaviour is not being recorded in the Luxemburg EPC. Presumably it is the predominant cause of the spread of the data, which we still observe in Figure 2. However, from other sources we can estimate the standard deviation of the distribution of "true" user behaviour parameters and take it as an estimate of the error that we make when calculating the demand with standard specifications. Figure 3 shows frequency distributions of millions of winter room temperature measurements, mean room temperatures ϑ_{int} increasing by 4 °C from buildings built prior to 1978 to passive houses while the temperature spread between rooms within the same flat is reduced considerably[14].

Obviously real room temperatures in buildings tend to spread significantly about the Luxemburg EPC standard specification of 20 °C, the mean value of the total sample in Figure 3[15] has been estimated to $\overline{\vartheta}_{int}$ = 19,0 °C and the sample standard deviation $\sigma(\vartheta_{int})$ = 3,3 °C.

There is no comparable data for Luxemburg but it seems an acceptable approximation to estimate the error in calculated EPC demands from uncertainties in room temperature in German dwellings. Ideally standard specifications of user behaviour parameters in EPCs should have been defined as mean values of frequency distributions from random samples. Thus, we identify the standard specifications with the true mean of B_k and its known error $\sigma(B_k)$

$$B_k^{std} = \overline{B}_k \pm \sigma(B_k) \tag{9}$$

taking advantage of the standard deviation's invariance under changes in location of the random variable B_k: $\sigma(B_k + const) = \sigma(B_k)$.We further assume that these values of user behaviour parameters apply for a single dwelling unit, while in multifamily dwellings they average to values of the building, that approximate the standard specifications better with the standard error of the mean $\sigma(\overline{B}_k) = \sigma(B_k)/\sqrt{n_{DU}}$.

We estimate the error propagation of these uncertainties on calculated demand from the Gaussian Law of Error propagation, which is strictly speaking valid only for the distributions of user behaviour parameters to be Gaussian. Besides room temperature ϑ_{int} we include three other parameters of user behaviour, that are to be specified in Luxemburg EPC, namely the thermally effective window ventilation rate n [1/h], specific internal heat gain q_{int} [W/m²] and the specific domestic hot water demand q_{DHW} [kWh/m²a]. Calculated demand may then be considered as a function of these variables

$$q_{f,D} = q_{f,D}(\vartheta_{int}, n, q_{int}, q_{DHW}, x_1, \ldots, x_m) \tag{10}$$

and other variables x_m, i = 1, … , M of course, f.i. describing the physical building, which are supposed to have been specified with reasonable accuracy, uncertainties being neglected for this analysis. Provided that, the uncertainty of the calculated demand is given by equation (11).

$$\sigma(q_{f,D}) \tag{11}$$

$$= \sqrt{\left(\frac{\partial q_{f,D}}{\partial \vartheta_{int}} \cdot \sigma(\vartheta_{int})\right)^2 + \left(\frac{\partial q_{f,D}}{\partial n} \cdot \sigma(n)\right)^2 + \left(\frac{\partial q_{f,D}}{\partial q_{int}} \cdot \sigma(q_{int})\right)^2 + \left(\frac{\partial q_{f,D}}{\partial q_{DHW}} \cdot \sigma(q_{DHW})\right)^2 + \ldots}$$

The uncertainties in user behaviour variables are estimated from external sources (f.i. as shown in Figure 3) or from educated guess as depicted in Table 2 (Left).

A considerable average uncertainty in the independent variable $q_{f,D}$ of 25 % arises from the assumed spread in user be-

14. Building Research Establishment Ltd. (2013): Energy Follow-Up Survey 2011 – Report 2: Mean household temperatures, BRE report number 283078 prepared by BRE on behalf of the Department of Energy and Climate Change (DECC),UK, December 2013.

15. Franz Schröder (2017): Note, METRONA Wärmemesser Union GmbH, München, 2017.

Table 2. Left: Assumed uncertainties of user behaviour variables. Right: Average relative uncertainties of the calculated demand according to Luxemburg EPC Δq/q for different dwellings due to uncertainties in user variables.

Variable		σ(x)
Room temperature	ϑ_{int} [°C]	±3,3 °C
Thermally effective window ventilation rate	n [1/h]	±30 %
Specific internal heat gain	q_{int} [W/m²]	±30 %
Specific domestic hot water demand	q_{DHW} [kWh/m²a]	±30 %

Dwelling	Δq/q	Number of observations
Single-family houses (SFH)	30 %	2,788
Small Multi-family houses (sMFH)	22 %	938
Multi-family houses (MFH)	10 %	681
All houses	25 %	4,407

Data Source: Luxemburg EPC Register, Luxemburg Ministry of the Economy, IWU (DB4_eceee).

haviour. The question arises then of what are the effects on the above regression analysis?

REGRESSION IN THE ERRORS-IN-VARIABLES MODEL

Standard regression models assume that the independent variables have been determined exactly. With the analysis of user parameters in mind we have to assert that this is not the case. If we were to include user behaviour into our regression model as good as possible we would have to consider so called errors-in-variables models[16] at least for the calculated EPC demand.

We assume that $q_{f,D,i}$ was the true demand. It is unknown though, since actual user behaviour is unknown. We further assume $q^{EPC}_{f,D,i}$ to be our best measure of the true demand but it comes with a "measurement" error δ_i

$$q^{EPC}_{f,D,i} = q_{f,D,i} + \delta_i \qquad (12)$$

due to the spread in user behaviour. Let us consider a simplified version of regression equation (7) with $Ln(q^{EPC}_{f,D,i})$ being the only independent variable. Using the asymptotic of the ordinary least squares estimate, the amount of inconsistency due to measurement errors can be determined as

$$\lim_p(\beta_1) = b_1 \frac{\sigma^2\left(Ln(q_{f,D,i})\right)}{\sigma^2\left(Ln(q_{f,D,i})\right)+\sigma^2(\Delta_i)} < b_1 \qquad (13)$$

Hence the estimator of the slope coefficient, β_1, is always smaller in magnitude than the true value b_1, since variances are non-negative and the reliability ratio $\lambda=\sigma^2_{true}/(\sigma^2_{\Delta} + \sigma^2_{true})<1$ always is smaller than 1. This is called the attenuation bias. This explains partly what we observe in Table 1 (left): A shallow slope of β_1=0,47 instead of a physically expected b_1~1. Matters become more intricate with more independent variables, details lie beyond the scope of this paper.

There is not enough data at hand at the moment in order to derive the reliability ratio, but this should be a matter of independent studies. Provided that λ can be specified from independent data sources, a corrected estimator $\beta_1' = \beta_1/\lambda$ may be derived.

Unbiased regression functions are useful tools to derive calibration functions for calculated demands from simplified models to measured consumptions, as shown in the following chapter. This is particularly important in scenarios, when reliable consumptions including uncertainties are supposed to be predicted considering different paths of refurbishment action in the building stock.

Statistical Analysis of calculated Energy Demand and measured Consumption for non-residential Buildings in Germany

The research project "Teilenergiekennwerte von Nichtwohngebäuden" (TEK)[3] within the ENOB research program of the Federal Ministry for Economic Affairs and Energy (BMWi) delivered a database consisting of 92 records of existing non-residential buildings (see Table 3) and the TEK-Tool[7] for demand calculations was developed, based on the general terms of German DIN 18599, though implementing various simplifications in the algorithms. The TEK-database contains detailed information on properties of the building envelope, energy efficiency of technical installations, user behaviour, measured energy consumptions and calculated energy demands.

Heating and Hot Water

Regression analyses similar to the ones mentioned above were applied in order to analyse the observed discrepancy between calculated energy demand for heating and domestic hot water and actual energy consumption in the sector of non-residential buildings.

Three different calculation schemes were applied: *Real-Real* with data on user behaviour and building geometry collected as realistic as possible, *Std-Real* with standard specifications on user behaviour as of DIN 18599-10 and *Std-simplified* with a simplified model of the building envelope geometry in addition to standard specifications of user behaviour.

As can easily be seen from the best fit straight lines in a *simple regression* model in Figure 4 calculation is in better accordance with measurement the more realistic values of the input variables have been chosen. Data points in the Std-simplified-scheme are similarly spread as the Luxemburg EPC data though, also showing heteroscedasticity.

Following our rationale, for the further derivations we will focus on the Std-simplified-scheme which is our preferred candidate for calculations of many buildings in scenarios of a building stock for example. From physical reasoning and fol-

16. Jeffrey M. Wooldridge (2003): Introductory Econometrics: A Modern Approach, 2e, Thomson Learning – South-Western, Mason, Ohio 45040, USA, p. 305 ff., 503 ff.

Table 3. Distribution of the 92 non-residential buildings in the TEK-database for different classifications.

Age band	Number of buildings	Net floor area	Number of buildings	Use	Number of buildings
before 1918	10	up to 1.000 m²	3	Office	23
1919–1948	5	1.001 to 5.000 m²	36	Trade	11
1949–1977	38	5.001 to 10.000 m²	29	University	19
1978–1994	26	10.001 to 30.000 m²	20	Hotel	8
1995–2001	7	> 30.000 m²	4	School	15
after 2002	6			Event	16

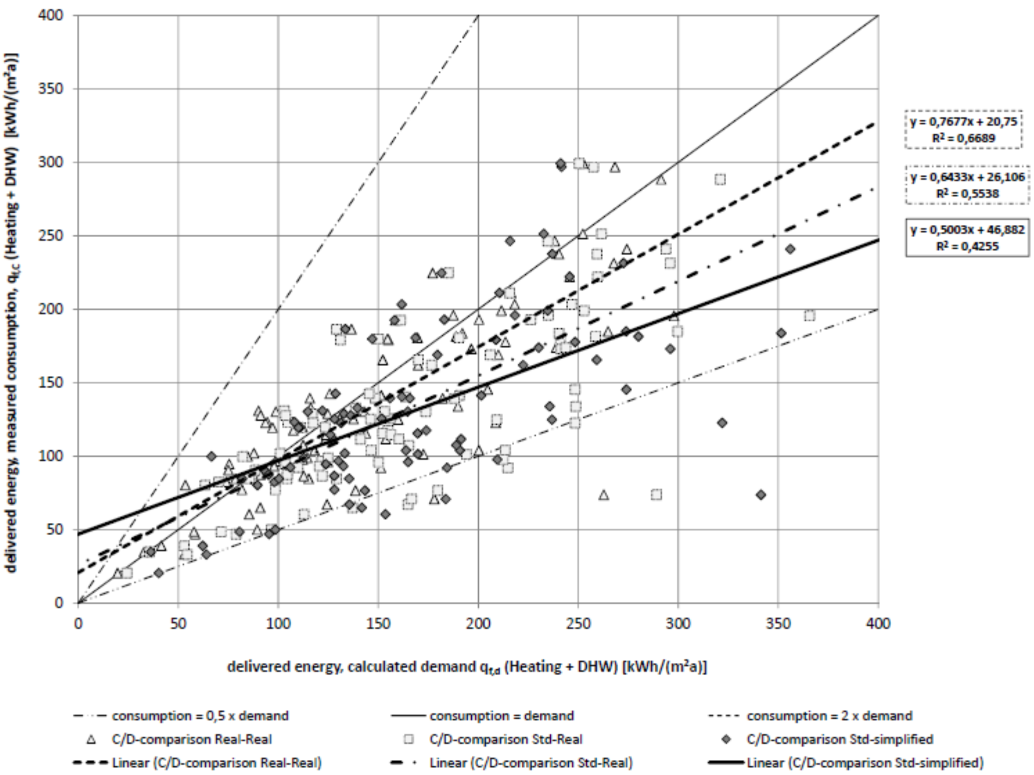

Figure 4 Plot of measured consumption over calculated demand of the buildings' delivered energy for heating + domestic hot water for three calculation schemes (Real-Real, Std-Real, Std-simplified) and best fit straight lines in a simple regression model.

lowing the procedure outlined in the previous chapters we propose the *multiple regression* equation

$$\ln\left(\hat{q}_{f,C}\right) = \beta_0 + \beta_1 \cdot f_{winvent,area} + \beta_2 \cdot \Delta q_{\mathrm{int},std-real} + \beta_3 \cdot \Delta t_{use,std-real} + \beta_4 \cdot \Delta \vartheta_{\mathrm{int},std-real} + \beta_5 \cdot \ln\left(q_{f,D}^{Std-simpl.}\right) \quad (14)$$

We take advantage of the in depth building assessments in the TEK-project delivering momentary values of user parameters and their deviation from standard specifications in DIN 18599-10: differences of standard and real heat gain $\Delta q_{\mathrm{int},std-obj}$, use time $\Delta t_{nutz,std-obj}$, room temperature $\Delta\vartheta_{Raum,std-obj}$. $f_{winvent,area}$ is a percental value of the building's net floor area with window ventilation, while $q_{f,D}^{Std-simpl.}$ denotes calculated delivered energy demand in the Std-simplified-scheme and $\hat{q}_{f,C}$ the estimator of measured consumption.

Thus we figure the estimation function

$$\hat{q}_{f,C} = q_{f,D}^{Std-simpl.\,\beta_5} \cdot e^{\beta_0+\beta_1 \cdot f_{winvent,area}+\beta_2 \cdot \Delta q_{\mathrm{int},std-real}+\beta_3 \cdot \Delta t_{use,std-real}+\beta_4 \cdot \Delta\vartheta_{\mathrm{int},std-real}} = f_{C/D}\left(q_{f,D}^{Std-simpl.}\right) \cdot q_{f,D}^{Std-simpl.} \quad (15)$$

rendering a calibration function $f_{C/D}$

$$f_{C/D} = \frac{\hat{q}_{f,C}}{q_{f,D}^{Std-simpl.}} = \left(q_{f,D}^{Std-simpl.}\right)^{\beta_5 - 1} f_{use} \quad (16)$$

that is plotted over $q_{f,D}^{Std-simpl.}$ in Figure 5.

Thus with a simplified calculation model of TEK and a handful of parameters characterizing actual usage of a building we get a pretty good estimation of the building's presumable consumption, the adjusted Coefficient of determination R^2=63 % and an estimated standard error $\hat{\sigma}(\hat{q}_{f,C})$ =31 %. The slope estimator β_5 in the multiple regression model becomes β_5 = 0,81, which comes pretty close to 1.

Errors in variable

Let us return to a simple regression model with only $\ln(q_{f,D}^{Std-simpl.})$ as an independent variable. Results in the Real-Real-Scheme may be considered as true values of the demand figured independently of the Std-simplified-Scheme, since advantage has been taken of on-site measurements of parameters of user behaviour, though momentarily only and thus error prone also, and a more realistic geometry model. As a plausibility check we

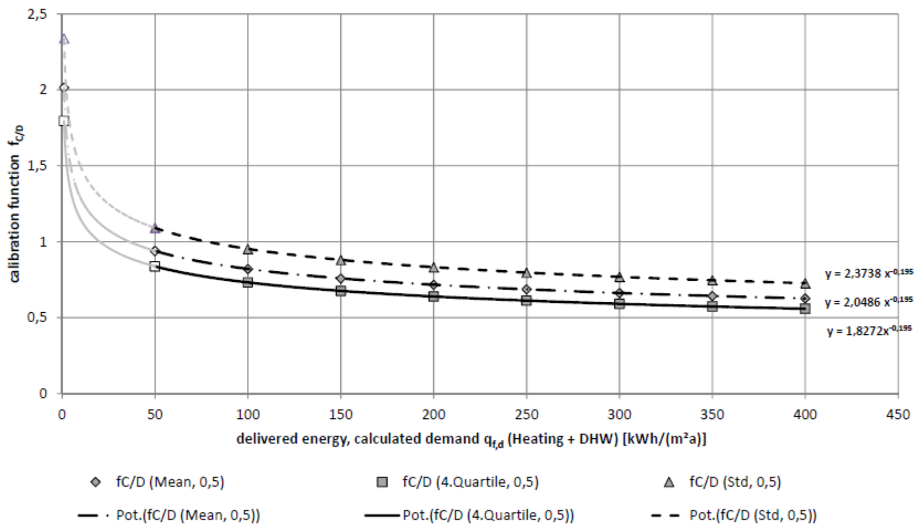

Figure 5. Calibration function $f_{C/D}$ over calculated demand in Std-simplified-scheme with 50 % window ventilated area and various deviations of user behaviour parameters from standard specifications assumed: No deviation (Std; 0,5), mean of deviations (Mean; 0,5) and mean of the 4th quartile of deviations (4. Quartile; 0,5).

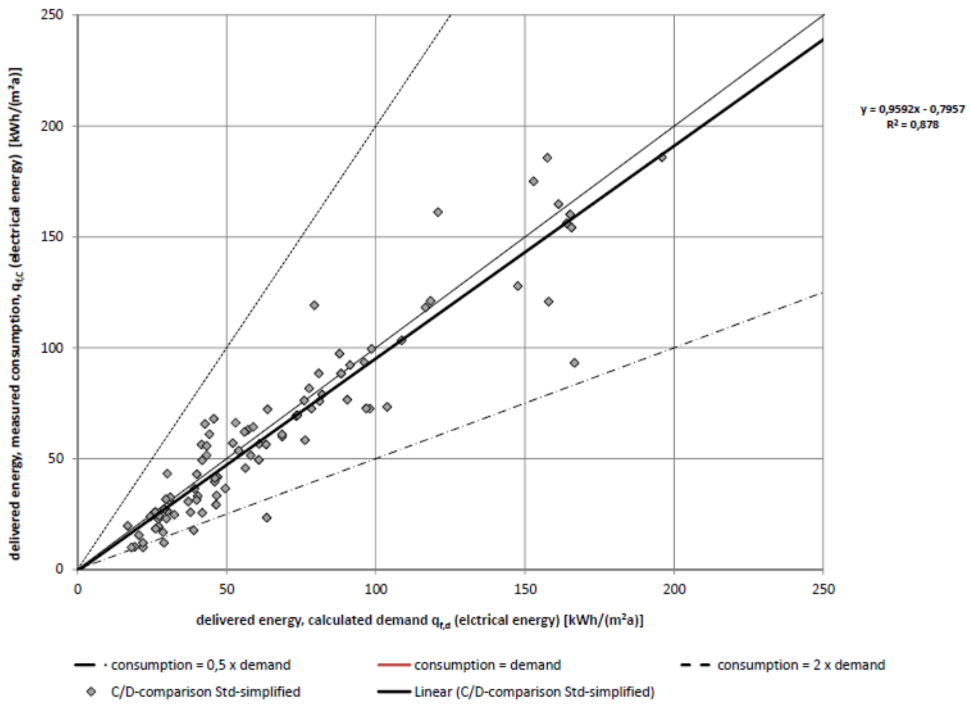

Figure 6. Plot of measured consumption over calculated demand of the buildings' delivered electrical energy for the Std-simplified-scheme.

adapt the error-in-variable model in equation (12) $\ln(q_{f,D,i}^{Std-simpl.}) = \ln(q_{f,D,i}^{real-real}) + \Delta_i$. With the Pearson correlation coefficient $\rho(\ln(q_{f,D,i}^{real-real}),\Delta_i) = 0{,}39$ we assume the two quantities to be uncorrelated, the classical errors-in-variables assumption. The reliability ratio then turns out to be λ=0,81. Thus, the error of the calculated demand in the Std-simplified-Scheme seems to cause most of the observed bias in the slope coefficient β_5.

Electrical Energy

Interesting is the fact that for electrical energy no such problems were found in the TEK-project. As figure 6 shows even with standard specifications of user behaviour and a simplified geometry model for the building envelope calculated demands and measured consumptions are in reasonable relation.

Conclusions

EPCs are made to inform about the energy-related quality of buildings and to certify compliance with Energy Performance Ordinances irrespective of user behaviour and climate parameters. However, specific values of calculated energy demand for heating and domestic hot water deviate considerably from measurements f.i. in energy bills.

In energy consulting and the economic assessment of energy savings measures, on the other hand, most often similar calculation schemes are used as in EPCs but with actual values of user behaviour and climate parameters and adjustment of physical building parameters within their usual ranges of uncertainty. A considerable effort comes along with this, but calculation results are much more consistent with measurements.

Either way discrepancies between measured energy consumption and calculated demand cannot be avoided. Statistical analysis can provide calibration to real consumption and realistic estimates of the uncertainties in the calculations. The new EPC in Luxemburg includes this information for building owners.

These calibration functions may be improved by the errors in variable model. The distribution of user behaviour parameters should be quantitatively analysed with the objective to realistically define standard specifications as the mean values of typical samples including standard errors as a measure of their spread.

For buildings stocks' analyses simplified calculation models with well-defined standard specifications including uncertainties and calibration functions are one method of choice to predict the future energy consumption of the building sector in scenario calculations. Quantifiable uncertainties are an essential in order to use these scenario results as basis for decision making in the political arena. Statistical methods as exemplified above should be considered as standard in scenario calculations to achieve this. Prerequisite are databases with representative samples of building data on measured consumption and calculated demand.