APPLICATION OF PARTIAL SAFETY FACTORS IN BUILDING ENERGY PERFORMANCE ASSESSMENT

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ABSTRACT

In practise many buildings show significant deviation between the predicted annual energy consumption and the actual energy consumption. One of the main reasons for the discrepancy is the difference between the assumptions made during the calculations and the actual conditions including occupants' behaviour.

This paper presents two methods to consider uncertainty and spread of energy consumption calculations in practise, namely a simulation approach and a safety factor approach.

A simulation approach is investigated using Monte Carlo analysis where a comprehensive list of stochastic input parameters is evaluated by sensitivity and uncertainty analysis to develop a significantly reduced set of stochastic input parameters.

The safety factor approach provides a means of enforcing the maximum allowed energy consumption in the building code by multiplying the maximum limit by a partial safety factor to obtain a design energy consumption that can be used for the usual energy calculations.

INTRODUCTION

In general there is a need for consideration of spread and uncertainty in practical energy calculation. However, to facilitate the practical application it is necessary to consider simpler and robust methods. The purpose of the paper is to develop simplified methods to enable modellers in practise to perform more accurate calculations and to provide estimates of uncertainty.

The methods may comprise at least two levels of detail and corresponding use, namely a more detailed level using Monte Carlo simulation to get an accurate estimate of the uncertainty by direct consideration of input distributions, and another - and simpler - approach where the main purpose is to facilitate proper and robust energy design that complies with building code requirements.

As to the *simulation approach* the purpose is to determine at least the mean value and standard deviation and, preferably, also the distribution of the energy consumption. In the extreme, it requires information of the distribution of all input parameters as wells as the mutual correlation before performing a Monte Carlo simulation. This is both unnecessary and also unreasonably costly in terms of simulation time and the required information of the input distributions and correlation. Thus, there is a need to simplify the process. This paper considers an approach where the importance of numerous parameters is considered by screening sensitivity analysis and global sensitivity analysis leading to a reduced number of input parameter distributions that may provide a sufficiently accurate output distribution. The sufficient number of stochastic input parameters is determined by uncertainty analysis and Kolmogorov-Smirnov goodness-of-fit tests.

Regarding the *safety factor approach* the main idea is not to determine detailed information of the uncertainty of the energy consumption but rather to provide a robust and easy-to-use tool for the building designers that may consider the spread indirectly and at the same time ensure a reasonably high probability of not exceeding the energy requirements of the building code. Some of the analyses related to the simulation approach are used to establish a foundation of the safety factor approach.

METHOD AND RESULTS

In the following the two different approaches are presented and applied on a specific building and building model.

Building model

The energy consumption is calculated using the energy calculation programme *Be06* from the Danish Building Research Institute (Aggerholm and Grau, 2007) which is an application of the EN 15217 (2007) and ISO 13790 (2008) standards complying with the requirements in the Energy Performance of Buildings Directive (EU, 2002; Aggerholm and Grau, 2007). This is in fact the programme that is used for documentation when buildings are approved by the Danish authorities regarding the energy consumption requirements in the building code.

To demonstrate the two approaches a residential building in shape of a single-family detached house is applied, see Figure 1. The building is chosen due to the fact that it is an example building provided together with the *Be06* User's Guide and thus quite well-known among Danish consultants and also due to the fact that the construction is typical for Danish residential buildings. The building area is 180 m^2 of conditioned space with a circumference of 63.3 m and 0.4 m cavity walls. Room height is 2.4 m and storey height is 2.7 m. In the following analyses it is assumed that the building is mechanically ventilated and heated by means of district heating. As a starting point, the *U*-values for ceiling, floor and walls are 0.12, 0.11 and 0.22 W/(m^2K), respectively.

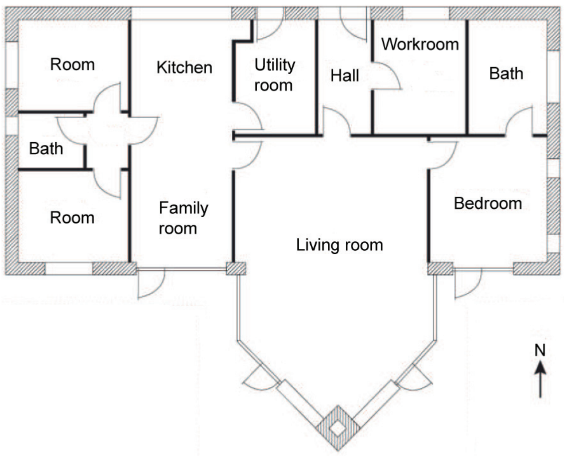

Figure 1 Sketch of modelled residential building in shape of a single-family detached house (Aggerholm and Grau, 2007).

Simulation approach

The aim of the simulation approach is to apply Monte Carlo simulation to obtain detailed information of the energy consumption distribution. Ordinary energy calculation, e.g. performed according to EN 15217 (2007) and ISO 13790 (2008), comprises a very high number of input parameters that may potentially influence the spread of the output distribution. The order of magnitude is around 100 parameters. To enable practical application it is necessary to investigate what parameters are the most important and reduce the number of stochastic parameters substantially to facilitate the application while still maintaining accurate estimations.

In the following qualitative screening sensitivity analysis and quantitative global sensitivity analysis are performed to rank the input parameters according to importance. The screening is used for ranking and also for a first indication of potential strong correlation or non-linear effects. The global analysis is used for ranking, too, but may also be used for apportioning the output variance to the related input parameters. Together with uncertainty analyses, evaluated by goodness-of-fit tests on distributions, the combined analyses are used to give advice on what input parameters to include as stochastic parameters while treating the remaining deterministic.

The screening method of Elementary Effects (Morris, 1991; Saltelli et al., 2000) is applied in this work. The method, which can be seen as an extension of a derivative-based screening method, can be characterised as a screening method with global characteristics. The method has been applied in several areas of building sciences e.g. natural night ventilation (Breesch and Janssens, 2004).and thermal building simulation (De Wit, 1997).

One of the most important activities in simulation work is the determination of input distributions. When proper distributions are found they can be reused as long as the underlying data does not change. Some input parameters may be mutually correlated which, in theory, requires that measures of mutual correlation should be established and applied in the simulations. In practise correlation is most often disregarded due to the difficulties of both finding and applying the correlations.

In the present work input distributions are established for 75 input parameters applied in the energy calculations. The distributions are determined using a combination of measurements, questionnaires, literature, theoretical considerations, and also educated guesses depending on the accessibility of material in each case (see Table 4). The list is a gross list from where relevant parameters are drawn for instance depending on whether the building is heated using an oil-fired boiler or by district heating. In the present case 57 parameters are applied in the sensitivity analyses and also in the most comprehensive uncertainty analysis. Due to lack of information the input parameters are assumed to be independent, i.e. uncorrelated. This assumption is discussed later on.

The results of the screening analysis are presented in Figure 2 where each input factor is shown as a function of the mean value of the absolute values of the elementary effects μ^* and the standard deviation σ. The 10 most important parameters are summarised in Table 1 and ranked according to importance.

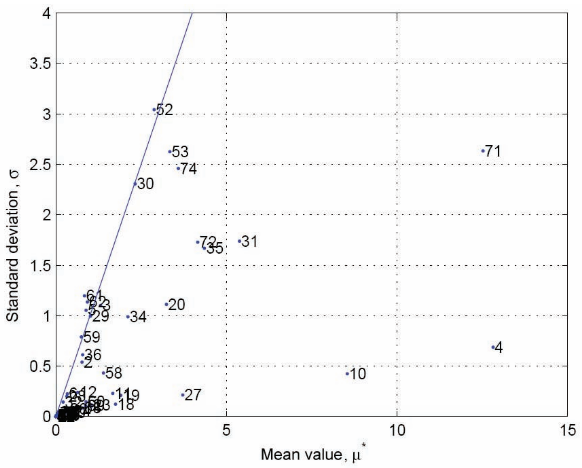

Figure 2 Results from screening SA. Numbers refer to Table 4.

Table 1
Most important parameters from screening SA (unit kWh/(year·m^2)). Numbers refer to Table 4.

No	Parameter	μ^*	σ
4	Set-point space heating	12.8	0.7
71	Nat. vent. winter, occupied	12.0	1.7
10	Hot water consumption	8.5	0.4
31	Angle of horizon	5.4	1.7
35	Appliances heat load, occupied	4.4	1.7
72	Nat. vent. winter, unoccupied	4.2	1.7
27	Window *U*-value	3.7	0.2
74	Natural ventilation summer	3.6	2.5
53	Numerical reference parameter (heating)	3.3	2.6
20	Wall *U*-value	3.2	1.1

A quantitative sensitivity analysis is performed using the Fourier Amplitude Sensitivity Test (FAST) method applying the same parameters and distributions as in the screening case. FAST is a variance based method based on performing numerical calculations to obtain the expected value and the variance of a model prediction (Saltelli et al., 2000). The numerical calculation is a transformation that converts a multidimensional integral over all uncertain model inputs into a one-dimensional integral using a search curve. A decomposition of the Fourier series representation is applied to assess the individual input parameters' contribution to the overall model variance.

The results are expressed in first order effects by means of the first order sensitivity index, S_i, and corresponding total order sensitivity index, S_{Ti}. A total of 71,193 realisations are performed in the quantitative analysis. In the present case time consumption performing the quantitative analysis is found to be approximately 100 times as high as for the screening analysis. Table 2 shows the results ranked and in comparison with the corresponding screening analysis.

Table 2
Comparison of screening and quantitative sensitivity analysis for the 10 most important parameters, respectively. Numbers refer to Table 4.

Screening SA			Quantitative SA		
No	μ^*	σ	No	S_i	S_{Ti}
4	12.8	0.7	71	0.283	0.315
71	12.0	1.7	4	0.274	0.303
10	8.5	0.4	10	0.137	0.158
31	5.4	1.7	20	0.030	0.064
35	4.4	1.7	30	0.028	0.060
72	4.2	1.7	31	0.038	0.058
27	3.7	0.2	53	0.023	0.055
74	3.6	2.5	52	0.019	0.054
53	3.3	2.6	27	0.032	0.054
20	3.2	1.1	35	0.031	0.052

In Figure 3 results of the uncertainty analysis are presented. The uncertainty is determined via the cumulative distribution function for the yearly energy consumption found by means of Monte Carlo analysis. Results from three different numbers of realisations are shown. For 5000 realisations the following statistics are found; mean value μ = 118.3 kWh/(m^{2}year), median x_m = 117.7 kWh/(m^{2}year), standard deviation σ = 11.1 kWh/(m^{2}year), and coefficient of variation δ = 9.4 %. Apart from those statistics it is possible to estimate the probability of a certain energy consumption using the cumulative distribution function directly.

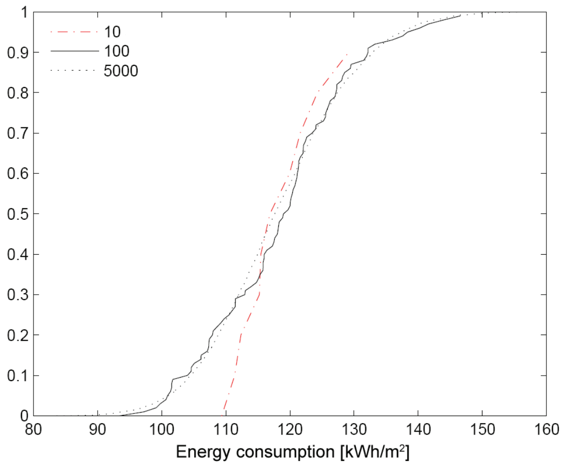

Figure 3 Uncertainty analysis of yearly energy consumption via the cumulative distribution function for three different numbers of realisations. Based on the application of 57 input distributions.

In the Appendix an analysis is performed regarding the sufficient number of stochastic input parameters and the minimum number of realisations in each simulation. The analysis indirectly includes a test of the, often applied, assumption of normally distributed energy consumption.

Safety factor approach

Energy consumption of buildings of the same size is subject to varying levels of spread due to different building types, energy design principles, construction practises, and occupants' behaviour. Using today's energy calculation practise of building energy consumption calculation by a deterministic approach using average values will inevitably lead to building populations that, on the average, may fulfil the building code requirements but for a substantial proportion actually show much higher energy consumption.

When the society wants to reduce the energy consumption substantially it is obviously of great importance to be able to actually control the energy consumption and ensure that the probability of failure, i.e. exceeding the building code maximum energy consumption, is sufficiently low.

There may be drawn a parallel between energy calculation and structural building design. As to structural design the society accepts only an extremely low probability of failure. This probability of structural failure depends on building type and building use among others (EN 1990, 2007). For structural safety consideration partial safety factors are applied to ensure low probability of failure. Both material strength and loads profiles are multiplied by factors reducing the strength and increasing the load, respectively, to acknowledge the spread and meet the requirements.

The aim of the proposed safety factor approach is to establish a simple and easy-to-use method that actively, and in the design phase, considers the influence of the substantial spread of the energy consumption and ensures a sufficiently low probability of failure to meet the energy design requirements of the building code.

The simplified safety factor approach presented in the following is a pilot study of the idea of a partial safety factor applied for energy consumption calculations. The overall purpose of the proposed method is to develop a relatively simple and robust way to make sure that the energy consumption of the built environment fulfils some requirements to the actual energy consumption considering the actual spread.

The method introduces a single "partial safety factor" that reduces the allowed energy consumption according to the spread and according to the accepted probability of failure (i.e. the energy consumption exceeding an enacted maximum limit), see Figure 4. Future work may expand the single safety factor into more factors which is done for load and strength in the structural case.

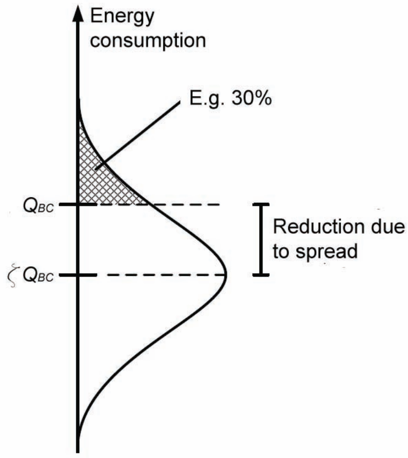

Figure 4 Building code's maximum energy consumption, Q_{BC}, reduced by factor ζ to obtain a design energy consumption, $\zeta \cdot Q_{BC}$, to be applied for practical energy calculations.

Thus, the purpose is to make sure that probability of the energy consumption X exceeding the maximum limit, Q_{BC}, is below a certain value κ, see Figure 4, i.e.

$$P(X \leq Q_{BC}) = 1 - \kappa \qquad (1)$$

$$Q_{BC,\mu} = \varsigma(\kappa, \delta) \cdot Q_{BC,\kappa} \qquad (2)$$

It is assumed that the energy consumption is normal distributed $X \sim N(\mu,\sigma^2)$ in order to apply the calculation rules related to the standard normal distributions and appropriate transformations (Ayyub and McCuen, 2002). This important assumption is supported by the previous analysis and findings in the Appendix. Utilising the transformation between the normal distribution and the standard normal distribution $Z \sim N(0,1)$

$$Z = \frac{X - \mu}{\sigma} \qquad (3)$$

and

$$P(X \leq x) = \Phi(z) = 1 - \kappa \Rightarrow z = \Phi^{-1}(1 - \kappa) \qquad (4)$$

where $\Phi(z)$ is the cumulative distribution function of the standard normal. z can easily be found from standard statistical tables, spreadsheet functions or the like. Introducing the spread via the coefficient of variation $\delta = \sigma / \mu$

$$\varsigma = \frac{\mu}{x} = \frac{\mu}{\mu + \sigma z} = \frac{\mu}{\mu + \mu\delta z} = \frac{1}{1 + \delta\Phi^{-1}(1-\kappa)} \qquad (5)$$

Table 3 provides some examples of ζ for different probabilities of failure, κ, and coefficients of variation, δ, representing the spread of the energy consumption.

Table 3
ζ-values for different probabilities of failure, κ, and coefficient of variations, δ (by formula (5)).

κ	δ		
	0.05	0.10	0.15
0.05	0.9240	0.8587	0.8021
0.10	0.9398	0.8864	0.8388
0.30	0.9744	0.9502	0.9271

The building in Figure 1 may be used as an example. The Danish building code accepts at present a maximum energy consumption of Q_{BC} = 82 kWh/(m^2·year) in this case. The specific building type and layout is found to have an approximate coefficient of variation of $\delta = 0.1$. If a probability of failure of $\kappa = 0.1$ is accepted, the safety factor $\zeta = 0.8864$ can be found from Table 3 or by formula (5). Thus, for practical calculations the design energy consumption is 0.8884·82 = 73 kWh/(m^2·year). Obviously, this would result in reduced energy consumption and would as such be subject to a political decision.

DISCUSSION AND RESULT ANALYSIS

Simulation approach

Numerous input parameter distributions are established for energy consumption calculation of a residential building in Table 4. By means of Kolmogorov-Smirnov testing (Appendix) it is found that by using approximately 10 stochastic input parameters and around 500 – 1000 realisations in each simulation the final result will deviate little from a comprehensive reference case of 57 stochastic parameters and 5000 realisations. Reasonable results can be found for even fewer parameters and realisations. Furthermore, it is found that the normal distribution provides an excellent description of the energy consumption.

This means that simulation can be undertaken using a significantly reduced set of stochastic parameters and a reasonable number of realisations thus providing valuable guidance for the practical use of Monte Carlo simulation when detailed information of the energy consumption is requested.

The three most important parameters are identified by screening and global sensitivity analysis to be

- set-point of heating, i.e. the occupants' preferred internal temperature
- natural ventilation in winter in the occupied period, i.e. infiltration, window and door opening, airing, etc.
- hot water consumption

The variability of the three parameters accounts for approximately 70% of the entire variation of the energy consumption. A list of several other parameters account for a significant but considerably smaller amount.

It is worth to note that the three most important parameters are all strongly related to occupants' behaviour. This strong influence of occupants is found in other investigations, too.

The screening sensitivity analysis, using the method of Elementary Effects, reveals that none of the input parameters shows significantly non-linear or correlation behaviour in the building energy consumption model. This is concluded by comparing the mean values, μ^*, and the standard deviations, σ, of the analysis results in Table 1.

Correlation of input parameters is ignored due to lack of information and, as a consequence, the input parameters are assumed statistically independent. The quality of this assumption may be questioned to some extent. Whereas hot water consumption may not at all be correlated with building orientation, infiltration and set-point for space heating may be somewhat related, and obviously the floor area and the ceiling area. Yet, in general it is felt that the assumption does not violate the overall conclusions. More research including measurements is needed to provide sound and detailed evaluation of the correlation issue.

Despite the fact that weather variability (external temperature, wind and solar radiation) may contribute strongly to energy consumption variability it is not included in the present work due to the fact that the present energy calculation method applies a fixed set of monthly weather data.

Safety factor approach

A simplified approach in shape of a safety factor is proposed. Using this approach the spread in energy consumption may be considered in a simplified way and an enacted probability of not exceeding a certain level of energy consumption may be enforced by the authorities. The method assumes normally distributed energy consumption which is verified in the Appendix.

The safety factor, ζ, is a function of two factors, namely the probability of exceeding a certain level of energy consumption, κ, and the coefficient of variation, δ, of the energy consumption. The probability κ should be determined in a combined technical and political process using considerations related to socio economics and environmental economics. It should obviously be considered together with the decided maximum level of energy consumption. The spread of the energy consumption considered via the coefficient of variation may be determined for a number of standard building types and energy designs etc. by means of comprehensive measurements and analysis. It may be determined easily by “standard tables” or by more elaborate documentation of energy design (for unusual buildings “outside category” stricter requirements or more advanced calculations may be required). In that way the method may contain an important incentive to work for better and more robust buildings and energy design including the construction process. If the building owner documents a lower spread due to robust methods higher design energy consumption is permitted for the calculations.

This pilot study is only a first step. More work is required to investigate and establish a useful method for simple consideration of spread and uncertainty in practical energy design.

CONCLUSIONS

This paper presents two methods to consider uncertainty and spread of energy consumption calculations, namely a simulation approach and a safety factor approach.

A simulation approach is investigated using Monte Carlo analysis where a comprehensive list of stochastic input parameters is evaluated by sensitivity and uncertainty analysis to develop a significantly reduced set of input parameters and required number of realisations for the simulations. It is found that by using approximately 10 stochastic input parameters and around 500 – 1000 realisations in each simulation the final result will deviate little from a comprehensive reference case. Reasonable results can be found for even fewer parameters and realisations. Furthermore, it is found that the normal distribution provides an excellent description of the energy consumption.

The safety factor approach provides a means of enforcing the maximum allowed energy consumption in the building code by multiplying the maximum limit by the partial safety factor to obtain a design energy consumption that can be used for the usual energy calculations. The method assumes normally distributed energy consumption which is verified in the work. The safety factor, ζ, is a function of two factors, namely the probability of exceeding a certain level of energy consumption, κ, and the coefficient of variation, δ, of the energy consumption.

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Table 4
Input distributions
Type N is truncated normal distribution, L is truncated or modified lognormal distribution, and U is uniform distribution. Interval defines distribution boundaries; in case of the normal distribution μ is mean value and σ is standard deviation

No	Parameter	Unit	Type	Interval; μ; σ	No	Parameter	Unit	Type	Interval
1	Conditioned space	m^2	N	177.5 – 182.5; 180; 0.8	39	Airflow rate summer, occupied period	$l/s{\cdot}m^2$	N	0.55 – 1.25; 0.9; 0.12
2	Building heat capacity	Wh/m^2K	N	100 – 140; 120; 6.7	40	Airflow rate summer, unoccupied period	$l/s{\cdot}m^2$	N	0.55 – 1.25; 0.9; 0.12
3	Occupied period	h/week	N	84 – 168; 126; 14	41	Nominal boiler power	W	N	14.5 – 17.5; 16; 0.5
4	Set-point space heating	°C	N	20 – 24; 22; 0.67	42	Full-load efficiency	-	N	0.88 – 1.08; 0.98; 0.033
5	Set-point airing	°C	L	22 – 27; NOTE	43	Full-load temperature correction factor	$°C^{-1}$	N	0.0005 – 0.0025; 0.0015; 0.00033
6	Set-point night ventilation	°C	L	23 – 28; NOTE	44	Part-load load	-	N	0.27 – 0.33; 0.3; 0.01
7	Design supply-pipe temperature	°C	N	40 – 50; 45; 1.67	45	Part-load efficiency	-	N	0.96 – 1.18; 1.07; 0.037
8	Nominal pump power	W	N	30 – 50; 40; 3.3	46	Part-load test temperature	°C	N	32 – 38; 35; 1
9	Pump utilisation factor	-	N	0.3 – 0.5; 0.4; 0.033	47	Part-load temperature correction factor	$°C^{-1}$	N	0.0005 – 0.0025; 0.0015; 0.00033
10	Hot water consumption	$l/year{\cdot}m^2$	N	83 – 333; 250; 55.6	48	Idle loss factor	-	N	0.005 – 0.01; 0.0075; 0.002
11	Hot water temperature	°C	N	50 – 60; 55; 1.67	49	Part of idle loss to conditioned space	-	N	0.125 – 0.875; 0.5; 0.125
12	Hot-water tank heat loss	W/K	L	2.0 – 3.3; NOTE	50	Blower power	W	N	90 – 110; 100; 3.3
13	Length of hot-water tank supply pipe	m	N	0.6 – 1.4; 1.0; 0.13	51	Automation power	W	N	3.5 – 4.5; 4; 0.17
14	Supply pipe heat loss	W/mK	N	0.14 – 0.24; 0.17; 0.025	52	Reference time constant (heating)	h	U	1 – 100
15	Ceiling area	m^2	N	177.5 – 182.5; 180; 0.8	53	Numerical reference parameter (heating)	-	U	0.1 – 6
16	Floor area	m^2	N	153.5 – 158.5; 156; 0.8	54	Utilizable part of heat loss	-	N	0.025 – 0.175; 0.1; 0.025
17	Wall area	m^2	N	116.1 – 119.7; 117.9; 0.6	55	Boiler test temp. difference	°C	N	27 – 33; 30; 1
18	Ceiling *U*-value	W/m^2K	N	0.102 – 0.138; 0.12; 0.006	56	Full-load fraction relative to standby	-	N	0.27 – 0.33; 0.3; 0.01
19	Floor *U*-value	W/m^2K	N	0.088 – 0.132; 0.11; 0.0073	57	Water specific heat	MJ/m^3K	N	4.097 – 4.191; 4.145; 0.016
20	Wall *U*-value	W/m^2K	N	0.166 – 0.274; 0.22; 0.018	58	Air specific heat	kJ/m^3K	N	1.130 – 1.298; 1.214; 0.028
21	Foundation length	m	N	63.1 – 63.5; 63.3; 0.07	59	Angle factor	-	N	0.80 – 0.92; 0.86; 0.02
22	Length of window joints	m	N	90.7 – 92.1; 91.4; 0.22	60	Cold water temperature	°C	N	7 – 13; 10; 1
23	Foundation line heat loss	W/mK	N	0.096 – 0.144; 0.12; 0.0079	61	Reference time constant (cooling)	h	U	1 – 100
24	Window line heat loss	W/mK	N	0.02 – 0.04; 0.03; 0.0033	62	Numerical reference parameter (cooling)	-	U	0.1 – 6
25	Building orientation	°	N	± 2; 0; 0.67	63	Side shadows	°	N	± 2; 0; 0.67
26	Window area	m^2	N	3.275 – 3.345; 3.31; 0.012	64	[Not applied]			
27	Window *U*-value	W/m^2K	N	1.29 – 1.57; 1.43; 0.047	65	Heat exchanger power	W	N	14.5 – 17.5; 16; 0.5
28	Window glass fraction	-	N	0.58 – 0.62; 0.6; 0.0067	66	Heat exchanger heat loss	W/K	N	1 – 2;1.5; 0.17
29	Glass *g*-value	-	N	0.60 – 0.66; 0.63; 0.01	67	Automation and standby power	W	N	4.5 – 5.5; 5; 0.17
30	Solar shading factor	-	L	0.2 – 0.9; NOTE	68	Mechanical ventilation winter	$l/s{\cdot}m^2$	N	0.300 – 0.366; 0.333; 0.011
31	Angle of horizon	°	U	0 – 30	69	Heat exchanger efficiency	-	N	0.84 – 0.90; 0.87; 0.01
32	Angle of overhang	°	N	± 2; 0; 0.67	70	Specific fan power	kJ/m^3	N	0.86 – 0.98; 0.92; 0.02
33	Window recess	%	N	± 2; 0; 0.67	71	Natural ventilation winter, occupied period	$l/s{\cdot}m^2$	N	0.09 – 0.34; 0.13; 0.067

34	Occupant heat load	W/m^2	N	0.3 – 1.75; 1.0; 0.25	72	Natural ventilation winter, unoccupied	$l/s{\cdot}m^2$	N	0.05 – 0.3; 0.10; 0.067
35	Appliances heat load, occupied	W/m^2	N	0.5 – 3.7; 2.1; 0.53	73	Mech. vent. summer, occupied	$l/s{\cdot}m^2$	N	0.300 – 0.366; 0.333; 0.011
36	Appliances heat load, unoccupied	W/m^2	N	0.1 – 1.2; 0.6; 0.2	74	Natural ventilation summer	$l/s{\cdot}m^2$	N	0.345 – 0.789; 0.567; 0.074
37	Airflow rate winter, occupied	$l/s{\cdot}m^2$	N	0.05 – 0.55; 0.3; 0.083	75	Mech. vent. summer, unoccupied	$l/s{\cdot}m^2$	N	0.300 – 0.366; 0.333; 0.011
38	Airflow rate winter, unoccupied	$l/s{\cdot}m^2$	L	0.05 – 0.3; NOTE					

NOTE regarding lognormal distributions only (L). In each case a standard lognormal distribution L(μ,σ) is positively displaced and truncated to obtain the requested distribution. No 30 is a “reversed” lognormal distribution. Intervals for truncation are mentioned above.

No	μ; σ; positive displacement; peak frequency	No	μ; σ; positive displacement; peak frequency
5	0.3; 0.5; 21.95; 23	38	0.001; 1.75; 0.05; 0.1
6	0.3; 0.5; 22.95; 24	No	μ; σ; transformation of parameter no 30; peak frequency
12	0.01; 0.25; 1.25; 2.2	30	0.35; 0.55; $X_{Fc} = -(X/5 - 1)$; 0.8

APPENDIX KOLMOGOROV-SMIRNOV TESTS OF DISTRIBUTIONS

The two-sample Kolmogorov-Smirnov goodness-of-fit test is used to compare two distributions, in this case the original and the approximated normal distribution, and test whether the two underlying probability distributions differ. This is done by comparing the maximum difference of the two distributions, F, in question, using the Kolmogorov-Smirnov number

$$KS = \sup_x \left| F_1(x) - F_2(x) \right| \qquad (6)$$

The value of KS is compared by a so-called critical KS_α determined by the number of data n and the requested significance level, α, where $c(\alpha)$ is a coefficient that depends on the significance level (CRC, 2003)

$$KS_\alpha = c(\alpha) \cdot \sqrt{\frac{n_1 + n_2}{n_1 \cdot n_2}} \qquad (7)$$

In this case significant levels of α = 0.05 and 0.01 leads to $c(\alpha)$ = 1.36 and 1.63, respectively.

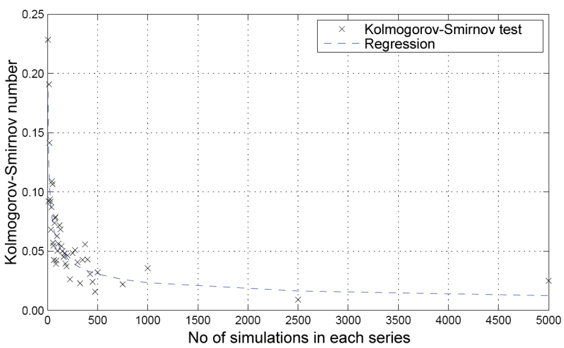

Figure 5 Kolmogorov-Smirnov goodness-of-fit test of number of simulations and of normal distribution. Each output distribution from simulation is compared with a corresponding normal distribution based on the mean value and standard deviation of the specific simulation.

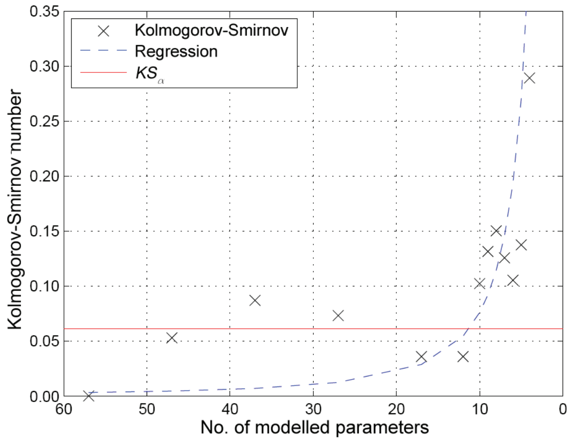

Figure 6 Kolmogorov-Smirnov goodness-of-fit test of number of stochastic input parameters. Each output distribution is compared with the reference distribution that comprises 57 parameters. In each case 1000 realisations are applied, KS level for α = 0.05 is indicated by the horizontal line.

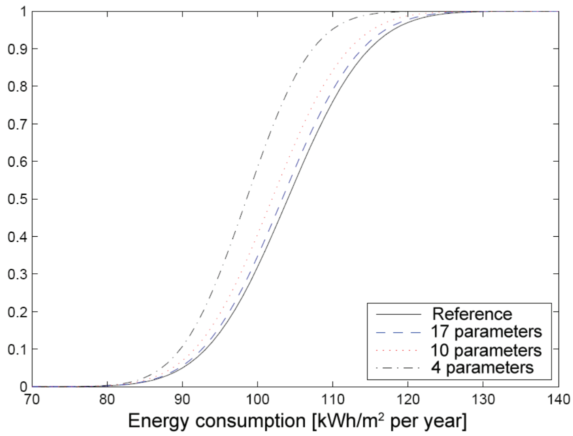

Figure 7 Cumulative distribution functions for the reference energy consumption (57 stochastic input parameters) and three different numbers of stochastic input parameters. Each distribution is a normal distribution based on the mean value and the standard deviation of the corresponding simulation.