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On incorporating uncertainty analysis in abstract building performance simulation tools

Christian Struck [1], Petr Kotek [2], and Jan Hensen [1]

[1] Technische Universiteit Eindhoven, Netherlands

[2] CVUT Technical University of Prague, Czech Republic

C.Struck@bwk.tue.nl

Abstract

Building Performance Simulation (BPS) is a powerful measure to educate the building design process. However, its use in practice is too large extends limited to the detailed design stage dedicated to the code compliance analysis of worked out design proposals. BPS is not much used to support the conceptual design stage (CDS). To date BPS – tools are regarded as pure analysis tools, which do not provide design information.

It is hypothesized that, when integrating uncertainty analysis techniques to existing BPS – tools (incremental research approach) valuable design information can be provided.

The paper gives an update on the process to integrate an uncertainty assessment capability to a tool specifically developed to support the conceptual design stage. The resulting prototype should be capable of providing information about the deviation of specific design parameters (simulation output) based on the uncertainties of the building concept specification (simulation input). In addition to the total uncertainties, the results also indicate sensitivities of the design parameters as a result of the concept specification variation.

This paper describes an approach to add extra-capabilities to legacy simulation tools and presents a comparison of uncertainties and total sensitivities calculated with one detailed design analysis (DDA) tool, IES, and one conceptual design analysis (CDA) tool , LEA. The main focus was herby the representation of material properties and its impact on the model uncertainty.

1. Introduction

Although practitioners assess the use of building performance simulation tools for conceptual design to have the potential to add value and to educate the design process, their use is limited. It is argued that the mismatch between the tool capabilities and the user's needs is one of the reasons explaining this phenomenon [1]. Considering the conceptual design stage one needs to be aware of its characteristics and their impact on the use of BPS – tools.

The detailed design stage is characterized by a limited number of design concepts with extensive parametric detail, which facilitates the use of DDA – tools. The CDS is characterized by a large number of design concepts with none to little parametric detail.

By applying DDA – tools, the limited amount of design information available requires assumptions to fill the gaps. The strategy deployed by CDA – tools, reduces the input detail to describe the building and its use to the crucial parameters governing energy demand and/or thermal comfort.

One example is the restriction to define more than one or two thermal zones, which traditionally represent spaces or groups of spaces within one building. Another simplification is the definition of the buildings thermal response by defining the building mass directly as number or by options as high and low. [2, 3] Furthermore it has been observed that CDA – tools frequently use fixed values to represent the surface heat transfer on building elements. A review of six BPS - tools, advertised as being of use from concept to detailed design, revealed that only two out of six, Energy 10 and h.e.n.k., come close to serving the needs of practitioners during the CDS [4]. Those tools represent analysis tools that allow the analysis of one design option at the time. The tool user is left to make interpretations of the numbers representing the tool output and to convert the analysis results to design information. Whilst one simulation might be sufficient for code compliance analysis, a greater number of simulations are required to perform parametric uncertainty and sensitivity studies.

Individual parameter sensitivity studies form one integral part of the concept evaluation phase in design practice. Introducing a capability to conduct building performance sensitivity studies the practitioner is supported with information about the total deviation (uncertainty) of design parameters. One example is the assessment of energy demand and thermal comfort deviations based on uncertainties of the concept specification (simulation input). Additionally, information indicating total sensitivities of the design parameters as a result of concept specification variations can be derived. By integrating total sensitivity analysis capabilities, the search space for potential concepts is expected to be explored more thoroughly and structured.

The uncertainties and total sensitivities of four parameters were calculated, with two tools addressing the impact of material property uncertainties for a CDA and DDA – tool. A tool performance comparison has been carried out. The four parameters compared are: annual demand for heating and cooling as well as peak heating and cooling loads.

2. Uncertainty analysis in building performance simulation

De Wit in [5] identified four potential uncertainties sources in BPS. He differentiated between numerical -, scenario-, specification-, and modeling uncertainty. The latter two, specification and modeling uncertainties, addressing the description of the building system, its properties and modeling abstraction level are addressed here.

The aim of earlier efforts to introduce uncertainty analysis techniques to BPS was to more realistically model the real on-site performance of buildings by using data that represent material performance variation factors as aging, moisture content and temperature variations [6]. Here, uncertainty analysis is used to provide design information, which is by the nature of the design stage, far from realistic but provides a strategy to systematically explore the performance of concept variations and their sensitivities.

This study considers uncertainties and total sensitivities. The output uncertainty represents the probability of the occurrence of the design parameter using confidence intervals.

The total sensitivities are derived from results based on an input sample matrix that uses different parametric values for each sample. Individual sensitivities, which can be derived from modifying only one parameter in each sample (Morris - analysis) have not been considered.

3. Methodology

A comparative study was conducted between two uncertainty analysis prototypes. The first prototype is based on a DDA – tool and is used as reference. The second prototype, under investigation, was built around a CDA –tool. Based on the software review the successor of h.e.n.k., LEA prerelease 0.9.3, was chosen for representing the category of CDA - tools. IESv5.5.1, an industry strength and extensively used DDA - tool was chosen to represent the category of detailed design analysis tools. As LEA is specifically designed to support practitioners with estimations of the instantaneous peak heat/ cooling load and annual energy demand for heating/cooling the analysis had to be limited to those four parameters.

3.1 Tool performance calibration - Bestest

To define a starting point for the tool performance analysis both selected tools were bestest-ed. The Bestest procedure allows an inter-software performance evaluation for a number of predefined cases by defining performance limits. The building model used for the tool performance analysis was the Bestest case 600 [7]. The case 600 represents a lightweight, one zone building with two south facing windows and 200W internal gains.

3.2 Prototyping

To facilitate the performance comparison, shells were built around the selected tools automating the simulation process. The shell around IES integrates four tools: Simlab, MS Excel, Automate and MS WordPad. The shell around LEA required the integration of Simlab, MS Excel and Matlab. The procedure being applied consisted of the following four stages:

1: Selection of uncertain parameters and identification of standard deviations.
2: Generation of the sample matrix applying Latin hypercube sampling.
3: Simulating the Bestest Case 600 once for each sample.
4: Results analysis and reporting

The building model definition is different for the two BPS – tools requesting different operation regimes for the prototypes. Whilst IES VE describes a building model by a set of files, LEA only uses one file containing information about model description and operation. This fact resulted in the need to only replace of two files containing the sample data prior the simulation, for IES VE. For LEA each sample to be processed required the generation of a new model description file.

3.3 Analysis criteria

Two criteria are proposed to evaluate the performance of LEA using IES as reference.

A: Total output uncertainties evaluation

The criterion is based on the assumption that due to the limited extend of parametric detail available a design proposal during the conceptual design, performs more uncertain than during detailed design. Subsequently, the LEA prototype performance can be assessed adequate when the total uncertainty of the considered design parameters is equal or larger than calculated by the IEA prototype.

B: Parameter sensitivity evaluation

The total parametric sensitivities indicate the impact of the concept specification variations on the design parameter. The LEA prototype is expected to perform adequate when the resulting sensitivities of the parameters describing the concept specification variations match qualitatively with the DDA – tool.

4. Specification uncertainties

The tool performance analysis considers material properties only. The first out of two reasons for this limitation is that publications by others, dedicated to the evaluation of the on-site performance of construction materials due to aging, moisture content and temperature changes, are available to extract standard deviations for a multitude of materials [8]. The second argument is the possibility to indirectly consider the impact of the modeling abstraction level by aggregating material properties representing building elements as is required for the CDA –tool.

Table 1 shows the material properties with their assigned standard deviations. For the complete set of data, including density and specific heat capacity, see Appendix A - Table A1.

4.1 The sample matrix

There are a number of techniques available to conduct a sensitivity analysis such as Monte Carlo -, differential sensitivity (Morris) analysis -, and stochastic sensitivity analysis, among others. The techniques differ in how the sample matrix is generated defining the starting point for the output generation. The Monte Carlo analysis, also referred to as total sensitivity or uncertainty analysis, is characterized by a sample matrix where each of the parameters considered is modified for every sample generated based on a selected sample distribution technique. Latin hypercube sampling was chosen as technique for the sample generation as it gives an improved coverage of the search space.

Table 1: Bestest case 600 - Absolute material properties and assigned standard deviations.

		Thickness (m)	Standard deviation	Conductivity (W/mK)	Standard deviation
Wall	Plasterboard	0,012	/	0,16	0,04[8]
	Fiberglas quilt	0,066	0,02[5]	0,04	0,016[8]
	Wood siding	0,009	/	0,14	0,015[8]
Floor	Timber flooring	0,025	/	0,14	0,0378[8]
	Insulation	1,003	/	0,04	0,016[8]
Roof	Plasterboard	0,010	/	0,16	0,04[8]
	Fiberglas quilt	0,1118	0.02[5]	0,04	0,01[8]
	Roof deck	0,019	/	0,14	0,0238[8]

MacDonald and Lomas state in [9,10] that after processing 60-80 samples the improvements in the accuracy of the standard deviation, using the Monte Carlo technique, are marginal. Both publications exclude the number of uncertain parameters to have an impact on the accuracy of the standard deviation of the results. Simlab 2.2 used as uncertainty analysis processor hints in [11] that the minimum number of samples should not be less than 1.5 – times the uncertain parameters considered. In order to comply with both statements and to achieve a reasonable accuracy in the results the number of samples chosen for the analysis was 196 for the conducted 10 parameter uncertainty analysis.

4.2 Modeling uncertainty

The modeling abstraction level has been included by aggregating input data. Parameter aggregation is one technique to reduce the input requirements for CDA – tools. Whilst IES allows the definition of materials using properties such as cp (specific heat capacity), δ (density) and k (conductivity), LEA only allows the definition of one aggregated parameter R_k describing the heat conduction through building elements. In order to facilitate an uncertainty analysis, the standard deviations of the individual properties had to be equally aggregated. Table 2 shows the thermal performance of building components using the aggregated thermal resistance R_k and corresponding standard deviation out of 196 samples.

Table 2: Bestest case 600 – Aggregated material properties and resulting standard deviation (196samples).

	Thermal Resistance (m^2K/W)	Standard deviation
Wall	1.79	2.04
Floor	25.25	21.98
Roof	2.99	3.78

5. Results

The results presented are structured following the analysis process. Preceding the uncertainty analysis, the results for the Bestest case 600 compliance checks are shown in Appendix B1 defining a starting point for the uncertainty analysis. The uncertainty analysis itself is structured in two parts. The first part is dedicated to the overall uncertainty and the second part to a comparison of the resulting model sensitivities. The overall uncertainties have been analyzed using the absolute values followed by an analysis of their normalized values for direct comparison of the standard deviations. The output parameters considered were the annual energy demand for heating and cooling as well as the peak heating and cooling loads.

The sensitivities have been considered for each of the four output parameter individually using the linear partial correlation coefficient (PCC). The PCC allows a sensitivity analysis of linear working systems excluding the effect of correlations between input parameters.

5.2 Absolute results

Figure 1 and 2 show the absolute range of results calculated across 196 samples. The points at either end of the error bar represent the absolute minimum and maximum values and the annotated squares and circles indicate the corresponding mean average.

As can be noticed the sample coverage between IES and LEA show similarities. However, differences are also noticeable. The entire range of the annual energy demand for heating calculated by LEA is shifted approx. 1MWh to the lower end of the scale compared to the results by IES. Furthermore, the coverage of the peak cooling loads calculated with LEA is significantly smaller than for IES.

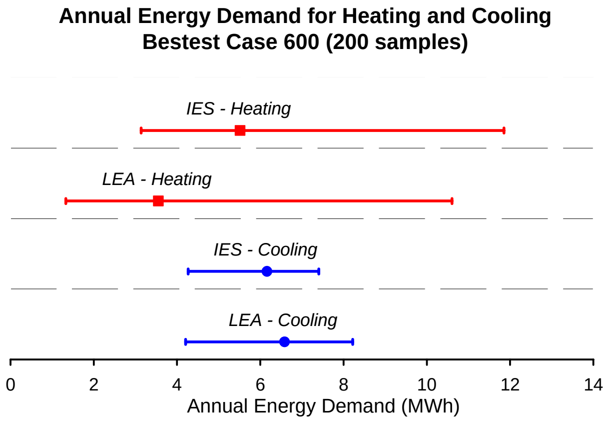

Figure 1: Annual Energy Demand,
Absolute Results, Comparison IES – LEA.

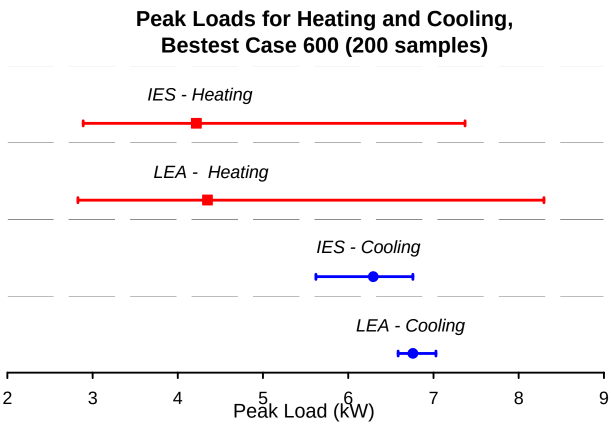

Figure 2: Peak Loads,
Absolute Results, Comparison IES – LEA.

5.3 Output uncertainties

The potential deviation of design parameters (output uncertainty) resulting from the concept variation specification (input uncertainty) is expected to be of great interest to practitioners. Referring to the Bestest case 600 at hand, the practitioner can at first glance recognize the probable occurrence of the four considered output parameter (see Table 3).

Table 3: Standard deviations (68% confidence interval) for absolute results across 196 samples.

	Annual Heating Demand [MWh]		Annual Cooling Demand [MWh]		Peak Heating Load [kW]		Peak Cooling Load [kW]	
	Min.	Max.	Min.	Max.	Min.	Max.	Min.	Max.
LEA	2.30	4.81	5.94	7.23	3.57	5.12	6.68	6.83
IES	4.26	6.77	5.67	6.65	3.56	4.88	6.13	6.46

To compare and evaluate the resulting uncertainties directly the results were normalized. Figure A2 and A3 - Appendix B2 visualize the absolute and normalized probability distribution for the annual cooling demands.

Table 4 summarizes the normalized standard deviations for the four considered design parameters for both tools. It can be noticed that all but one parameter, the peak cooling load, comply with the proposed total uncertainty evaluation criteria. The total parametric output uncertainties calculated with the CDA – tool are larger than the once for the DDA – tool. The standard deviation calculated for the peak cooling load using LEA is less than half the one calculated using IES. The observed disagreement reflects the results presented in the section dedicated to absolute results.

Table 4: Standard deviations for normalized output parameter
for direct comparison across 196samples.

	Annual Energy Demand for Heating	Annual Energy Demand for Cooling	Peak Heating Load	Peak Cooling Load
LEA	0.353	0.099	0.178	***0.011***
IES	0.227	0.080	0.156	0.026

Note: The highlighted parameter indicates non-compliance with the total uncertainty evaluation criteria.

5.4 Model sensitivity comparison

Once the total uncertainties of the design parameters have been established the interest of practitioners should focus on their minimization. To initiate the minimization exercise, it becomes necessary to identify sensitive and insensitive input parameters.

Based on finding in [10], the linear partial correlation coefficient (PCC) has been chosen to compute the systems parameter sensitivities. The PCC was selected as it was assumed that the system consisting of material property uncertainties and simulation model works linear. Furthermore, the PCC enables identifying the correlation of the input parameter and the output parameter, cleaned of effect caused by inter-correlations between input parameters [12].

Figures 3-6 visualize a comparison of PCC's derived from the uncertainty based total sensitivity analysis using SimLab 2.2. The graphs show the total sensitivities of the ten input parameter on the uncertainty of the design parameter. Whilst a large PCC indicates a high sensitivity, a small PCC indicates insensitivity. The bars have been ordered following the ranking of the CDA – tool. Whilst the top bar identifies the most sensitive input parameter the bottom bar shows the least sensitive parameter. The PCC's calculated with the DDA – tool have been arranged using the parameter ranking of the CDA – tool. The resulting ranking is therefore not strictly descending but enables a direct comparison of the parameter specific PCC between the tools.

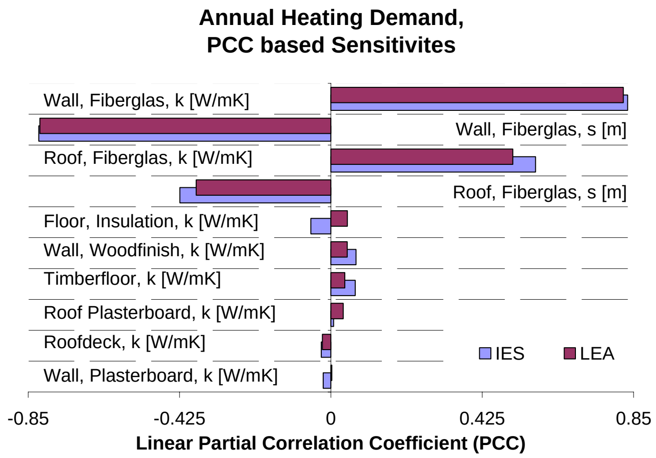

Figure 3: Annual Energy Demand for Heating,
PCC based Sensitivities, Comparison IES – LEA.

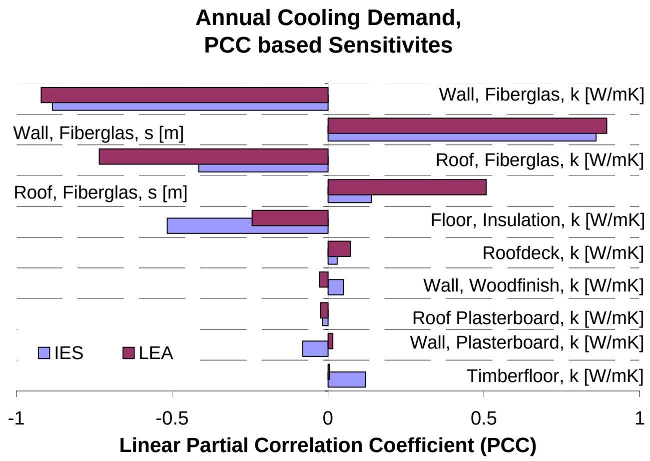

Figure 4: Annual Energy Demand for Cooling,
PCC based Sensitivities, Comparison IES – LEA.

5.4.1 Annual Energy Demand for Heating (ADH)

Figure 3 shows a good visual agreement between LEA and IES. The most sensitive parameter can be clearly identified as being the conductivity of the wall insulation followed by the thickness of the wall insulation. The third sensitive parameter is the conductivity of the roof insulation and the fourth sensitive parameter being the thickness of the roof insulation (see table A2). The remaining six parameters do seem to have a negligible small individual impact on the uncertainty of the ADH. The sensitivity ranking of the two tools is in good agreement.

Another fact that can be noticed is that parameters have opposing sensitivities for the two tools. For example, the conductivities of the floor insulation and wall plasterboard show a negative PCC for IES and a positive PCC for LEA. The phenomenon is refereed to as “Reversed sensitivities”, and is elaborated on in Appendix D.

5.4.2 Annual Energy Demand for Cooling (ADC)

Figure 4, showing the PCC based sensitivities for the ADC gives a less ordered picture than has been observed for ADH. For both tools five sensitive parameters can be identified. The parameter sensitivity ranking for the five most sensitive parameters is shown in table A3. Deviant to LEA, IES shows a different ranking. Whilst LEA results rank the conductivity of the floor insulation the fifth most sensitive parameter, IES ranks the same parameter third. The remaining two parameters are devalued one rank but keep their order. Reversed sensitivities can be noticed for the conductivities of wall wood finish and wall plasterboard.

The parameters that stand out as having an impact on the ranking describe the thermal behavior of the floor construction. The floor construction defined for the Bestest case 600 was set to decouple the space from the ground. Due to that reason the annual cooling demand and peak load react exceptionally sensitive to parametric changes.

5.4.3 Peak Heating Load (PHL)

Figure 5 shows a good visual agreement between LEA and IES. The most sensitive parameter can be clearly identified as being the conductivity of the wall insulation followed by the thickness of the wall insulation. The third sensitive parameter is the conductivity of the roof insulation and the fourth sensitive parameter being the thickness of the roof insulation (see table A4). The remaining six parameters do seem to have a negligible small individual impact on the uncertainty of the peak heating load. The sensitivity ranking of the two tools is in good agreement. Reversed sensitivities do not occur.

5.4.4 Peak Cooling Load (PCL)

Figure 6, showing the PCC based sensitivities for the PCL shows reduced similarities between the two tools compared to ADC. For both tools five sensitive parameters can be identified. However, whilst previously the top five ranks were occupied by the same parameters in changing order, different parameters occupy the top five ranks for the PCL. The parameter sensitivity ranking for the five most sensitive parameters is shown in table A5. Deviant to LEA, IES shows a different ranking. Whilst both show the same ranking for the same two most sensitive parameters the following ranks are occupied differently. Interesting is that IES ranks the timber floor conductivity seventh, whilst LEA results rank the parameter fourth. Furthermore, it surprises that IES ranks the roof insulation thickness fifth, whilst LEA ranks it ninth. Reversed sensitivities can be noticed for the conductivities of the wall plasterboard and roof plasterboard.

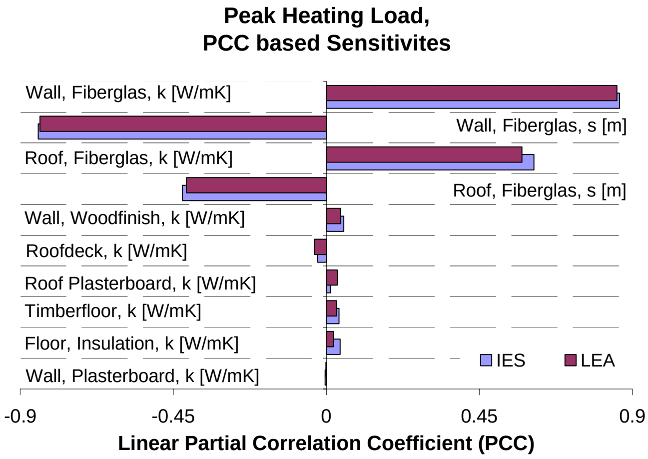

Figure 5: Peak Heating Load,
PCC based Sensitivities, Comparison IES – LEA.

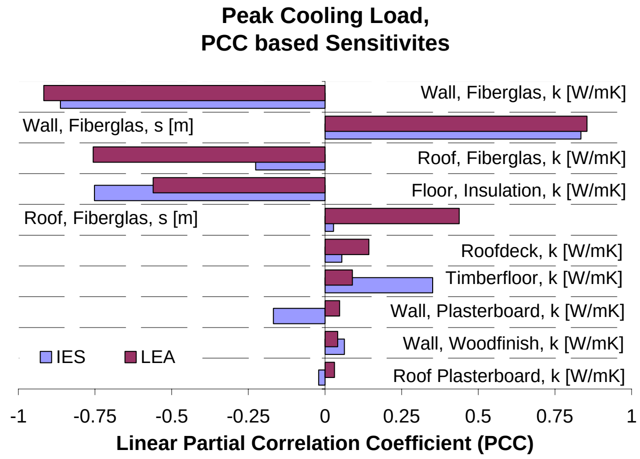

Figure 6: Peak Cooling Load,
PCC based Sensitivities, Comparison IES – LEA.

7. Conclusion

A study was undertaken to compare the performance of two prototypes dedicated to facilitate an uncertainty and total sensitivity analysis. The first prototype was build around one CDA – tool, LEA. The second prototype was based on one DDA – tool, IES. The aim was to identify if the tools compute comparable results. The uncertainties were introduced by assigning a standard deviation to ten material property parameters as analysis input. To assess the results, output uncertainties and total sensitivities, two criteria were defined, respectively.

Preceding the uncertainty and total sensitivity analysis both tools were bestest-ed. It was found that IES complies with all four performance limits, which are annual demand for heating and cooling as well as peak heating and cooling loads. Performing the test with LEA, it was found that three out of four performance limits could be met. The annual heating demand does not comply with the set limits. However, considering the tool's enhanced abstraction level it was decided to use it for the comparative study.

In order to compare the calculated uncertainties directly the results were normalized. The comparison does show that three out of four output parameters comply with the evaluation criteria. The fourth output parameter, the uncertainty of the peak cooling load calculated with LEA, shows an uncertainty less than half the uncertainty calculated with IES.

Comparing the total sensitivities calculated by both tools it was found that the tools show a good agreement for peak heating load and annual energy demand heating. It can be noticed that the same four parameters have a strong impact on the uncertainty of the output. The most sensitive parameters, in descending order, are: conductivity of the wall insulation material, thickness of the wall insulation material, conductivity of the roof insulation material and thickness of the roof insulation material. The remaining six parameters have a negligible small impact on the total output sensitivity.

The degree of agreement between the tools is reduced significantly for the output parameters annual energy demand for cooling and peak cooling load. Only the two most sensitive parameters show a good agreement for annual cooling demand and peak cooling load. The two most sensitive parameters are: conductivity of the wall insulation material and thickness of the wall insulation material. Furthermore, the impact of the input parameter reduces gradually from the most sensitive to the least sensitive parameter.

The varying impact of the input parameter on the uncertainty of the design parameter can be attributed to the tool specific representation of the surface heat transfer. Subsequently, it can be stated that LEA complies adequate with the results computed by IES.

It could be shown that the use of aggregated input parameter does not perturb the calculated uncertainties or total sensitivities.

Concluding the analysis it was found that the not Bestest compliant design parameter, annual heating demand has no impact on the use of the evaluation criteria.

8. Future work

The presented study is a first attempt to evaluate predicted uncertainties and total sensitivities by a CDA – tool. The uncertainties considered were limited to physical uncertainties (uncertainties related to material properties). Traditionally, those uncertainties are looked at to compute more accurate results, which are not the goal when using BPS – tools for conceptual design. Design uncertainties, such as wall to window area ratios or space surface area to volume ratios represent much better typical conceptual design questions. Therefore, future work will include the consideration of uncertainties related to typical conceptual design questions as well as expanding the comparison of CDA – tool predictions to other DDA – tools.

9. References

[1] Hopfe, C. J., Struck, C., Ulukavak Harputlugil, G., & Hensen, J. 2006. "Computational tools for building services design - professional's practice and wishes", Proceedings of the 17th Int. Air-conditioning and Ventilation Conference, 17-19 May, STP - Society of Environmental Engineering, Prague, p. 5 pages on CD

[2] Urban, B., 2006. “The MIT Design Advisor - a fast, simple tool for energy efficient building design” in Proc. SimBuild 2006, 2-4 August, Massachusetts Institute of Technology, Cambridge, MA/ USA, http://ceae.colorado.edu/ibpsa/ocs/viewabstract.php?id=186&cf=2

[3] Vabi BV. 2006, “User Manual h.e.n.k v3.0”, Handleiding h.e.n.k. v3.0, Document versie 1.0.0, http://www.vabi.nl/uploads/tx_userproducten/Handleiding_henk_3.pdf

[4] Hopfe, C. J., Struck, C., Ulukavak Harputlugil, G., Hensen, J., & Wilde, P. d. 2005. "Exploration of using building performance simulation tools for conceptual building design", in Proc. IBPSA-NVL conference, 20 October, Technische Universiteit Delft, p. 8 pages on CD

[5] De Wit, M.S. 2001. “Uncertainty in predictions of thermal comfort in buildings”, PhD Thesis, Delft University/ Netherlands.

[6] Struck, C., Hensen, J. 2006. “Uncertainty analysis for conceptual building design – A review of input data”, BauSIM 2006 Proceedings, pp.199 – 202, Munich/Germany.

[7] Judkoff, R. and Neymark, J. 1995. “International energy agency building energy simulation test (BESTEST) and diagnostic method”, National Renewable Energy Laboratory, Golden, CO.

[8] Clarke J.A., Yaneske P.P. and Pinney A.A. 1991. The harmonisation of thermal properties of building materials, Report TN91/6, BRE, Garston, Watford, UK

[9] MacDonald I. 2002. “Quantifying the effects of uncertainty in building simulation”, PhD Thesis, University of Strathclyde / United Kingdom.

[10] Lomas K.J. and Eppel H. 1992. Sensitivity analysis techniques for building thermal simulation programs, Energy and Buildings, Vol.19, pp.21-44.

[11] SimLab v2.2. Software Mask/ Statistical Pre Processor – Main Panel/ Practitioner’s Hint. Latin HyperCube

[12] Saltelli A., Tarantola S., Campolongo F., Ratto M. 2004. “Sensitivity Analysis in Practice: A Guide to Assessing Scientific Models”, John Wiley & Sons Ltd, West Sussex, UK

Appendix A – Material properties Bestest Case 600

Table A1: Bestest Case 600 – Material properties Wall, Floor, Ceiling

Wall	Thickness (m)	Conductivity (W/mK)	Density (kg/m^3)	Specific heat capacity (J/kgK)
Plasterboard	0,012	***0,16***	950	840
Fiberglas quilt	***0,066***	***0,04***	12	840
Wood siding	0,009	***0,14***	530	900
Floor				
Timber flooring	0,025	***0,14***	650	1200
Insulation	1,003	***0,04***	-	-
Roof				
Plasterboard	0,010	***0,16***	950	840
Fiberglas quilt	***0,1118***	***0,04***	12	840
Roof deck	0,019	***0,14***	530	900

Note: The material properties highlighted in Table A1 in have been subject to the uncertainty analysis.

Appendix B – Results

Appendix B1: Bestest case 600 analysis results for IES and LEA

The Bestest case 600 was used to calibrate the base line models for the tool performance analysis. Figure A1 indicates the results obtained for both tools, IES VE and LEA. The error bars indicate the Bestest performance limits. The annotated squares and triangles represent tool specific results for annual energy demand for heating and cooling as well as peak heating and cooling loads.

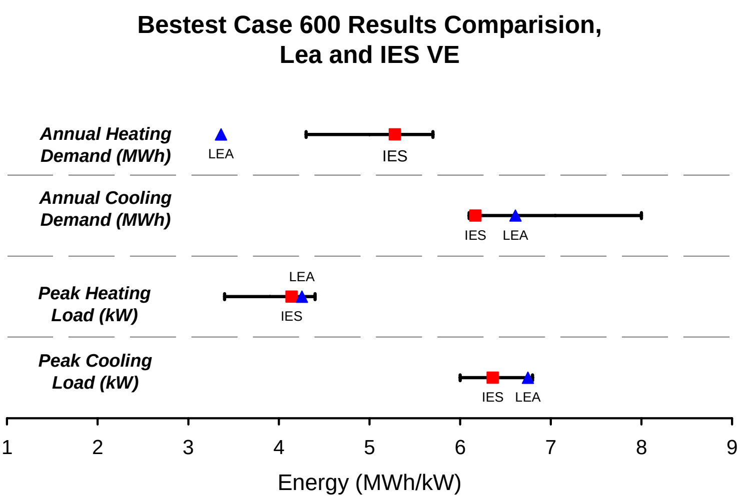

Figure A1: Bestest Case 600 Results, Comparison IES – LEA.

As can be noticed the results for both tools lay well within the limits for the parameters peak heating and cooling as well as for annual energy demand for cooling. The annual energy demand for heating calculated for LEA stays well below the minimum performance limit.

The Bestest procedure suggest to consider qualification cases for compliance checks and in case of disagreements between the result the use of diagnostic cases to isolate its source [7]. The consideration of diagnostic cases is beyond the scope of the current study and has not been reported on. Bearing in mind that LEA, a CDA – tool, working with abstracted input data it was concluded that complying with three out of four performance criteria is sufficiently accurate for conducting the proposed study.

Appendix B2: Absolute and normalized probability distribution for the annual cooling demand

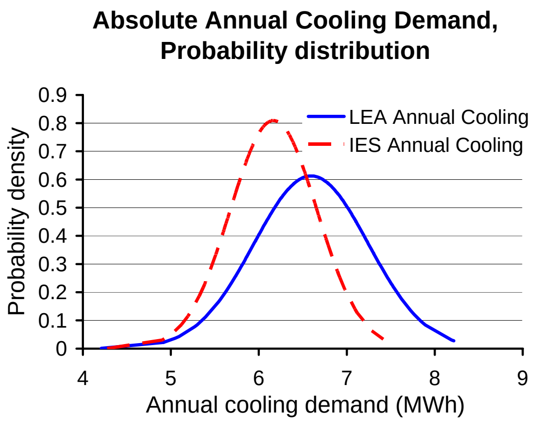

Figure A2: Annual Energy Demand for Cooling, Absolute Results, Comparison IES – LEA.

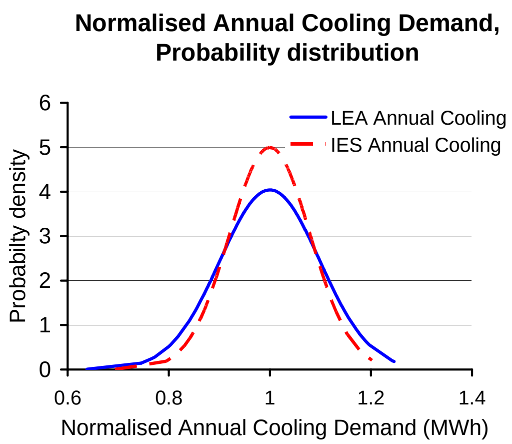

Figure A3: Annual Energy Demand for Cooling, Normalized Results, Comparison IES – LEA.

Appendix C – Total sensitivity parameter ranking

Annual energy demand for heating

Table A2: ADH Top 4, Most sensitive parameters, Ranking comparison.

Input parameter	Ranking	
	LEA	IES
Wall, Fiberglas, k	1	1
Wall, Fiberglas, s	2	2
Roof, Fiberglas, k	3	3
Roof, Fiberglas, s	4	4

Annual energy demand for cooling

Table A3: ADC Top 5, Most sensitive parameters, Ranking comparison

Input parameter	Ranking	
	LEA	IES
Wall, Fiberglas, k	1	1
Wall, Fiberglas, s	2	2
Roof, Fiberglas, k	3	4
Roof, Fiberglas, s	4	5
Floor, Insulation, k	5	3

Peak heating load

Table A4: PHL Top 4, Most sensitive parameters, Ranking comparison.

Input parameter	Ranking	
	LEA	IES
Wall, Fiberglas, k	1	1
Wall, Fiberglas, s	2	2
Roof, Fiberglas, k	3	3
Roof, Fiberglas, s	4	4

Peak cooling load

Table A5: PCL Top 5, Most sensitive parameters, Ranking comparison.

Input parameter	Ranking	
	LEA	IES
Wall, Fiberglas, k	1	1
Wall, Fiberglas, s	2	2
Floor, Insulation, k	3	4
Timber floor, k	4	7
Roof, Fiberglas, k	5	3

Appendix D - Sensitivity inconsistency

The algebraic sign (plus/minus) in front of the PCC indicates the direction of the parameter specific impact. For example, an increase of the wall insulation conductivity increases the annual heating demand and an increase of the wall insulation thickness reduces the annual heating demand. It was expected that the PCC's for both tools for the same parameter show the same algebraic sign to indicate the direction of impact. However, a number of input parameters show opposing algebraic signs in front of the PCC. Table A6 identifies the parameter showing sensitivity inconsistencies between LEA and IES of concern.

Table A6: List of parameters showing reversed sensitivities between IEA and LEA.

Heating		Cooling	
Annual demand	Peak load	Annual demand	Peak load
Wall, Plasterboard, k	/	Wall, Plasterboard, k	Wall, Plasterboard, k
Floor, Insulation, k	/	Wall, Wood finish, k	Roof Plasterboard, k

The most sensitive parameters are defined by PCC's with the same algebraic sign for each of the output parameter. At the same time the algebraic sign occurs self-explanatory reversed, when comparing input parameter specific PPC's for annual heating and cooling as well as peak heating and cooling. Following the above a consistency check was conducted for the parameters identified with reversed sensitivities to identify the tool specific behavior of the parameter. Table A7, identifies the parameter and associated tool computing a unidirectional impact of PCC on annual heating and cooling demand as well as peak heat and cooling load.

Table A7: Sensitivity inconsistencies, Parameters resulting in a unidirectional impact across annual demand/ peak loads.

	IES	LEA
Annual demand	Wall, Plasterboard, k	Wall, Plasterboard, k
	Wall, Wood finish, k	
	Floor, Insulation, k	
Peak load	Wall, Plasterboard, k	Roof Plasterboard, k

It can be noticed that the unidirectional impact only occurs for parameters describing the heat transfer for internal or externally exposed layers. So an explanation could be sought in the methodology the tools of representing the surface heat transfer, subsequently acting on energy demand and peak loads.