An Analytical Review of Tools and Methods for Energy Performance Simulation in Building Design

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Abstract

With increasing restrictions on energy demands in buildings, Building Energy Performance Simulation (BEPS) tools have been rapidly evolving since their first appearance in the early 1960s. Attempts to merge BEPS with the building design process have faced a number of challenges related to tool technicalities, user-friendliness, and data availability and handling. Thus, a number of practice-based tools have been developed, targeting different types of audience and decision making stages. Also, within academic research, a number of approaches have been adapted from other fields; such as computing and statistical research methods, aimed at assisting early design stage decision making. This study is part of a wider PhD research on the use of BEPS tools in informing architectural decisions in the early design stages. The study covers twofold objective of the larger research through establishing the state of the art in energy modelling tools, to define a categorization and identify recent and emerging trends in their development and application in practice. After performing an investigation into the currently available tools in practice and research, an extensive critical review of the published research in the field of building energy simulation was performed to capture the emerging trends in BEPS between 2008 and 2019. The review resulted in a categorization of 64 tools. It also concluded that emerging trends in the development of BEPS are showing increasing concern for aiding early design decision making. This is evident in the increasing number of tools targeting architects, and those aimed at usage at the early design stage. Also, a variety of tool-formats such as plug-ins have emerged for a higher level of engagement with the design process. Moreover, 66 publications adopting one or more emerging trending energy simulation methods were critically reviewed and listed. Results show a number of trending methods such as sensitivity and uncertainty analysis aiming at overcoming early design decision uncertainties. Also, the cloud-simulation method was found to enable instant simulation results, and artificial intelligence related methods such as genetic algorithms and artificial neural networks were found to assist the optimization and energy prediction process with higher accuracy.

Keywords: Building energy performance, simulation, tools, categorization, trends

1. Introduction

The Architecture, Engineering, and Construction (AEC) industry is undergoing increasingly stringent restrictions regarding energy consumption rates in buildings. The involvement of Building Energy Performance Simulation (BEPS) is increasingly being encouraged at the earlier design stages, as it is here where decisions with the largest impact on the building energy performance are taken (IEA, 2008). BEPS could be described as replicating an aspect of the energy performance of a building through a virtual computational model (De Wilde, 2018). Energy simulation is based on processing a number of thermal parameters, while mimicking building-element heat transfer, in order to calculate the expected energy consumption within a given time interval (Attia, 2012).

The first signs of computer-based BEPS are believed to have appeared in the USA in the early 1960s for designing underground shelters (Kusuda, 1999). Since then, a number of BEPS tools have been developed, targeting services engineers, for calculating technical requirements related to HVAC systems. The aim then was to specify suitable mechanical systems with minimal or no impact on fundamental architectural design decisions, as fuel then was considered inexpensive and the environmental impacts were not yet seriously being considered (Bachman, 2003). With the oil crisis in the 1970s, limitations to energy usage have been increasing. Tools then started to be used for validating architectural decisions at late stages in the design process. By the late 1980s, with the realization of the importance of earlier design decisions, BEPS's evolved to assist decisions taken at different design stages (Augenbroe, 1992). Some of the developed tools targeted architects considering them key decision makers in the early stages (Attia et al., 2009). The concept was that running simulations is more economical than the consequent operational energy costs of the building as a result of poor design (Hensen, 2008). By the end of the 1990s, there were a number of attempts at merging BEPS within the architectural design process such as 'Rijnland Office' and 'ECN Building' in the Netherlands (De Wilde et al., 1999). However, BEPS' integration was found to be significantly more complicated when compared to the smoothness of merging CAAD in the industry (Punjabi and Miranda, 2005). BEPS tools were originally designed to be used by engineers as verification tools at late stages when there is enough data available for use in energy models and simulations. In contrast, earlier design stages are more driven by architects' decisions which by necessity are freer of performance constraints and give rise to increased design and building performance uncertainties. At early stages, designers need user-friendly tools that are capable of providing quick feedback to cope with fast design iterations (Attia, 2012). By the start of the 21st Century, novel trends regarding BEPS tool development and application within practice and research emerged to encompass the nuanced requirements of different audiences at different stages. Novel methods such as cloud-simulation and plug-in options started to emerge to assist the design decision making processes. Notwithstanding, there remain significant barriers to their further adoption, but recent developments in tool capabilities and methods point towards new opportunities for the adoption and greater uptake of simulation tools at different stages in the design process.

Earlier studies were found to compare a number of BEPS software tools according to specific criteria. Based on a field survey, Attia et al. (2009) introduced a comparison between the user-friendliness of 10 simulation tools from architects' point of view, where IES-VE was perceived to be the most user-friendly. Also, it found that only 35 tools from the Building Energy Simulation Tools (BEST) directory were including architects as targeted users. In their comparison, Crawley et al. (2008) have focused on the technical capabilities of 20 BPS tools. The study did not include the usability, target groups nor timing in their comparison. Hopfe et al. (2005) compared 6 randomly selected tools that were meant to be used at the early design stage. The described studies conducted a comparison between limited numbers of tools, while including all building simulation types, without a special focus on the energy aspects. Our research strictly focusses on energy modelling and simulation tools in relation to architectural decision making, while investigating a broader range of tools and studies.

Following the research methodology, findings will be presented within two sections. The first discusses the criteria of the formulated categorization of 64 BEPS tools found to be related to energy analysis in relation to architectural design. The second part discusses the findings of 66 studies which were filtered through a process to extract the novel BEPS trends and methods emerging in the last 10 years.

2. Methodology

The authors have conducted two main areas of research focus. The first investigates currently available energy modelling tools used in the building design process. While the second involves conducting a systematic review of research databases in the period between 2008 and 2019 to extract emerging trends, conceptual approaches and prototype tools used in building energy modelling and simulation.

The primary investigated tool-directory was the BEST directory, formerly owned by the US Department of Energy (BEST, 2019). The directory has been chosen as a reliable international tool-reference according to previous studies (Hopfe *et al.*, 2005; Attia *et al.*, 2013; Yigit and Ozorhon, 2018). The directory includes 198 tools specialized in a number of simulation-related tasks. As the current research is mainly concerned with energy simulation tools that are impacting the architectural design decisions, a filtration criterion was applied; tools which are not related to energy analysis such as those specialised in; lighting performance; acoustics; and airflow, have been excluded. Part of the energy analysis tools related to; post-construction auditing; and billing calculations have been excluded as well as they are not used during the design process. As a final filtering step, tools designed for HVAC, duct and pipe sizing were also excluded as they are not directly related to architectural decisions. The BEST directory does not include all available tools, hence, a part of the systematic review was dedicated to investigating BEPS tools developed in academia. As this study is a part of a wider PhD researching the UK practice, tools used to comply with the energy conservation regulations in the UK were added, these are SBEM and SAP-related tools. The selected tools were then analysed based on the information provided by software developers, in addition to reviewing independent research on the tools.

The second mode of the investigation was undertaken to uncover related research studies into energy performance and building energy simulation methods using variations of a number of keywords related to: Building, Design, Energy, Performance, Simulation/Modelling; Software/Tool*/method*; and their synonyms. The search was mainly performed through the two databases Scopus and Web of Science.

Table 1 : Journal and conference BEPS-related publications

#	Journal	Results
1	Energy and Buildings	132
3	Sustainability	39
4	Applied Energy	35
6	Building And Environment	35
7	Automation In Construction	24
8	Journal Of BPS	25
9	Renewable & Sustainable Energy Rev.	21
10	Building Simulation	20
11	Journal Of Building Engineering	17
12	Energies	15
13	Energy	11
	Total	374

#	Conference	Results
1	Energy Procedia	96
2	IBPSA	90
3	ASHRAE Transactions	69
4	Procedia Engineering	32
5	Building Simulation Applications	29
6	Simulation Series	17
7	PLEA	13
	Total	346

After analysing the preliminary results, the emerging methods and trends were classified and the search terms were refined for subsequent review based on the following terms; Sensitivity analysis; Uncertainty analysis; Parametric analysis; Optimisation; Genetic algorithms; Artificial neural networks; and Cloud-Simulation.

Table 1 summarizes the numbers of investigated publications.

3. Results

The BEST directory includes a total of 198 BPS software tools. Among these, 55 tools claimed they include architects in their user groups. When this is compared with the findings of Attia and De Herde (2011), tools targeting architects have increased from 35 tools in 2010 to 55 in 2019. This supports the suggestion that there is a trend towards encouraging architects to use such tools for early decision making, (Wilde and Voorden, 2004; Attia *et al.*, 2012; Hensen and Lamberts, 2012). After applying the filtering criteria discussed in the Methodology, 42 tools (21%) from the BEST directory were found to criteria. An additional 12 practice-based tools were extracted from the reviewed publications; 9 tools were found to be developed for experimental academic studies (**Error! Reference source not found.**). The main finding regarding the total listed BEPS tools is that nearly the half (54%) are considering architects within their user groups (Figure 1), and 44% of the tools are developed to assist decision making at early phases of the design process (Figure 2).

Regarding the results of the second research mode, the initial publication review using the primary search-keywords provided 1,654 publications. Once filtered, a total of 720 studies were found to be related to the topic (

Table 1). These studies were then further filtered in relation to the earlier mentioned fields, where 66 publications have been analytically reviewed (Table 3 and Table 4).

4. Categorization of BEPS Tools

One aim of the study is to develop a categorization of the available BEPS tools having a direct impact on architectural decisions. The section will aim to categorize a wide range of tools with a focus on early stage. This shall include; user groups; design stage; tool format; and cloud-simulation (**Error! Reference source not found.**).

4.1. User groups

Two approaches could be commonly described regarding the use of BEPS tools in the design stage. The first where architects rely on in-house or outsourced expertise (usually from an engineering background) to undertake the energy analysis, then use the results to inform design decisions (Shelia J. Hayter, 2001). Another approach is for the architects to run the BEPS tools themselves providing real-time feedback through an iterative design process (Attia et al., 2009; Weytjens and Verbeeck, 2010). Engineers and architects are usually seen to be two distinctive user groups, where each has their own educational backgrounds, capabilities, and requirements while using BEPS tools (Alsaadani, 2013).

For engineers to execute energy simulation tasks, they require a clear set of data which should be pre-defined to a certain extent in a developed design and fabric specification, and they tend to deal with pure empirical input and output data in the form of numbers and schedules. On the other hand, architects tend to rely on intuition and rules of thumb, where their early application of BEPS is usually associated with a lack of defined data and specifications leading to high levels of uncertainty (Alsaadani, 2013). They also tend to rely on visual methods rather than empirical forms. Hence, tools for architects are expected to be more user-friendly and with simple Graphical User Interfaces (GUI) (Attia et al., 2009).

The investigated tools could be categorized into three groups; the first is highly technical and directed to engineers such as BSim (around 38% of the tools). This percentage would increase to around 80% when including HVAC design tools (not included in this study). Another group included tools targeting architects, where only 4 tools were found, such as Sefaira. An intermediate group contained tools targeting both user groups such as DesignBuilder (56%). This distribution is illustrated in Figure 1.

4.2. Design stage

Early design decisions are usually described to be the most critical in the building procurement process, and hence, earlier engagement of BEPS is commonly encouraged (MacLeamy, 2004; IEA, 2008). However, it is proclaimed that the majority of the BEPS tools are mainly developed for late verification purposes (Attia *et al.*, 2009; Hensen and Lamberts, 2012). Results show that 46% of the tools are aimed at conceptual design stage. This supports the idea that there is a movement towards developing more tools for early stages. The reaming 54% are developed for design verification purposes (Figure 2).

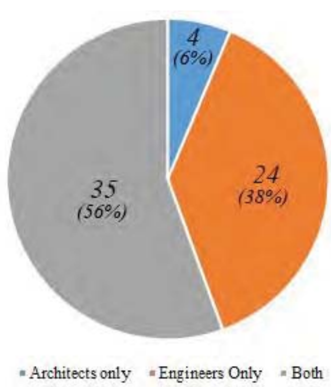

Figure 1: No. tools targeting user groups

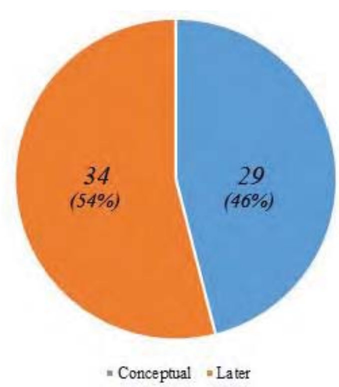

Figure 2: No. tools targeting design stages

Table 2: BEPS tools list

Type	#	Tool	User		Des. Stage		Dependency			Simulation Engine	Cloud Simulation	Parametric Analysis	Reference
			Architects	Engineers	Conceptual	Later	Stand-alone	Plug-in	3rd Party GUI				
Practice-based	1	AET	✓	✓		✓	✓			Own			BEST (2019) BEST Directory | Building Energy Software Tools. Available at: https://www.buildingenergysoftwaretools.com/
	2	Autodesk Insight	✓	✓	✓			✓	✓	Energy+	✓		
	3	BEAVER		✓		✓	✓			Own			
	4	Beopt	✓	✓	✓				✓	Energy+	✓		BEopt (2019) Building Energy Optimization Tool. Available at: https://beopt.nrel.gov/home
	5	Be10	✓	✓		✓				Own			BE10 (2019). Available at: http://www.viegandmaagoe.dk/
	6	BSim		✓		✓	✓			Own			BEST (2019) BEST Directory | Building Energy Software Tools. Available at: https://www.buildingenergysoftwaretools.com/
	7	BuildSimHub	✓	✓	✓		✓			Own	✓	✓	
	8	CAN-QUEST		✓		✓	✓		✓	DOE-2			
	9	CBECC-Com	✓	✓		✓			✓	Energy+			
	10	COMFEN	✓	✓	✓				✓	Energy+			
	11	COMFIE	✓	✓	✓		✓			Own			
	12	cove.tool	✓	✓	✓		✓			Own	✓		
	13	CYPETHERM Suite		✓		✓			✓	Energy+			
	14	DRQAT		✓		✓			✓	Energy+			BerkeleyLab (2019) Demand Response Quick Assessment Tool. Available at: https://drrc.lbl.gov/tools/
	15	DesignBuilder	✓	✓	✓			✓	✓	Energy+	✓	✓	BEST (2019) BEST Directory | Building Energy Software Tools. Available at: https://www.buildingenergysoftwaretools.com/
	16	DOE-2		✓		✓	✓			Own			DOE2 (2018) QUick Energy Simulation Tool. Available at: http://www.doe2.com/equest/
	17	EcoDesigner Star	✓	✓	✓			✓		Own			BEST (2019) BEST Directory | Building Energy Software Tools. Available at: https://www.buildingenergysoftwaretools.com/
	18	EFEN	✓	✓	✓				✓	Energy+			
	19	EnerCAD	✓	✓	✓		✓			Own			
	20	EnergyPlus		✓		✓	✓	✓		Own	✓		
	21	Energy Cost Calc.	✓	✓		✓	✓			Own			
	22	EnergyElephant	✓	✓		✓	✓			Own			
	23	Energy-10	✓	✓	✓		✓			Own			Attia, S. and De Herde, A. (2011), Early design simulation tools for net zero energy buildings: a comparison of ten tools, 12th IBPSA.
	24	ENERWIN Pro		✓		✓	✓			Own			BEST (2019) BEST Directory | Building Energy Software Tools. Available at: https://www.buildingenergysoftwaretools.com/
	25	eQUEST		✓		✓			✓	DOE-2		✓	DOE2 (2018) QUick Energy Simulation Tool. Available at: http://www.doe2.com/equest/
	26	ESBO		✓	✓		✓			Own			BEST (2019) BEST Directory | Building Energy Software Tools. Available at: https://www.buildingenergysoftwaretools.com/
	27	ESP-r		✓		✓	✓			Own			
	28	FineGREEN	✓	✓		✓			✓	Energy+			
	29	gEnergy	✓	✓	✓				✓	Energy+	✓		
	30	Green Building Studio	✓	✓	✓		✓	✓		DOE-2	✓		
	31	HAP		✓		✓	✓			Own			
	32	Honeybee	✓	✓	✓			✓	✓	Energy+		✓	
	33	IDA		✓		✓	✓			Own			
	34	IES VE	✓	✓	✓		✓	✓		Own			
	35	Ladybug	✓	✓	✓			✓		Energy+		✓	
	36	NovaEquer		✓		✓	✓			Own			
	37	N++		✓	✓				✓	Energy+	✓		EnergyModels (2013) N++ v2014 (E+ v8.1). Available at: http://energy-models.com/forum/n-v2014-e-v81-commercial-version-release
	38	OpenStudio		✓		✓		✓	✓	Energy+	✓		BEST (2019) BEST Directory | Building Energy Software Tools. Available at: https://www.buildingenergysoftwaretools.com/
	39	Parametric Analysis Too	✓	✓	✓				✓	Energy+		✓	OpenStudio (2019) Available at: http://nrel.github.io/OpenStudio-user-documentation/reference/parametric_analysis_tool_2/
	40	PHPP	✓	✓	✓		✓	✓		Own			PHI (2015) Passive House Planning Package (PHPP). Available at: https://passivehouse.com/04_phpp/04_phpp.htm
	41	Pleiades	✓	✓	✓				✓	Comfie		✓	BEST (2019) BEST Directory | Building Energy Software Tools. Available at: https://www.buildingenergysoftwaretools.com/
	42	Primero Comfort		✓		✓			✓	Energy+			
	43	SAP Tools: EES Design SAP	✓	✓		✓	✓			Own			BRE (2018) Approved software for SAP 2012. Available at: https://www.bre.co.uk/filelibrary/SAP/2012/SAP2012_9-92_software_2018-06-05.pdf
	44	iQ-Energy SAP											
	45	FSAP 2012											
	46	JPA Designer											
	47	SAPPER											
	48	SBEM	✓	✓		✓	✓			Own			BRE (2013) SBEM: Simplified Building Energy Model. Available at: https://www.bre.co.uk/page.jsp?id=706
	49	Sefaira	✓		✓			✓	✓	Energy+	✓	✓	BEST (2019) BEST Directory | Building Energy Software Tools. Available at: https://www.buildingenergysoftwaretools.com/
	50	SimulationX		✓		✓	✓			Own			
	51	Tas Engineering	✓	✓	✓		✓			Own			
	52	TRACE 700		✓		✓	✓			Own			
	53	TRNSYS		✓		✓	✓			Own			
	54	jess	✓	✓		✓			✓	Energy+	✓		EnSim (2019) JESS Online. Available at: http://cms.ensims.com/index.php/jess-online
	55	jePlus		✓		✓			✓	Energy+			BEST (2019) BEST Directory | Building Energy Software Tools. Available at: https://www.buildingenergysoftwaretools.com/
Research-based	1	BCVTB		✓		✓			✓	Energy+			Pang, X., Bhattacharya, P., O'Neill (2011), Real-time building energy simulation using energyplus and the building controls virtual test bed. 12th IBPSA.
	2	Building Des. Adviso	✓		✓				✓	DOE-2			Papamichael, K., LaPorta, J. and Chauvet, H. (1997) 'Building Design Advisor: automated integration of multiple simulation tools', Automation in Construction, 6(4), pp. 341-352.
	3	HENK		✓	✓		✓			Own			Itard, L. (2003), Henk, a software tool for the integrated design of buildings and installations in the early design stage. 8th IBPSA.
	4	HTB2		✓	✓			✓		Own			Jones, P., Lannon, S. and Li, X. (2013) Intensive building energy simulation at early design stage.
	5	MIT Design Advisor	✓		✓		✓			Own			Urban, B. and Glicksman, L. (2006) 'The MIT Design Advisor–A fast, simple tool for energy efficient building design', Proceedings of SimBuild, 2(1).
	6	NZEBO	✓		✓				✓	Energy+			Attia, S., Gratia, E., De Herde, A. and Hensen, J. (2013) 'Tool for design decision making: Zero energy residential buildings in hot humid climate', 13th IBPSA, pp. 3720-3727.
	7	Riuska		✓		✓			✓	DOE-2			Jokela, M., Keinänen, A., Lahtela, H., Lassila, K. and Oy, I.O.G. (1997) Building Simulation.
	8	SST2009	✓	✓		✓	✓			Own			Crobu, E., Lannon, S., Rhodes, M. and Zapata, G. (2013), Simple simulation sensitivity tool, 13th IBPSA.
	9	Virtual Design Studio	✓	✓	✓		✓			Own			Pelken, P.M., Zhang, J., Chen, Y., Rice, D.J., Meng, Z., Semahegn, S., Gu, L., Henderson, H., Feng, W. and Ling, F. (2013) Building Simulation. Springer.

4.3. Tool format

BEPS tools could be used as; stand-alone platform; plug-in within an authoring design tool; third-party GUI (Figure 3). Stand-alone software (55% of the tools) are mainly operated through own developed interface and rely on built-in calculation/simulation engines, such as EnergyPlus and DOE-2. Other tool-types are used as plug-ins within other CAAD authoring tools such as Sketchup and Revit. While some of the plug-in tools are limited to being in this format, some are originally stand-alone or 3rd party GUIs that have developed a plug-in to facilitate their integration within the design process. 12 tools (19%) were found to support a plug-in option. A number of research studies have suggested that one of the main reasons architects avoid using BEPS tools is poor user interfaces and data handling complexity. Hence, a number of tools were specifically developed as 3rd party GUIs combining one or more of the simulation tools; examples of those are N++ and eQuest. Also, there are some tools which were developed for academic research purposes such as ZEBO. These count for 40% of the tools.

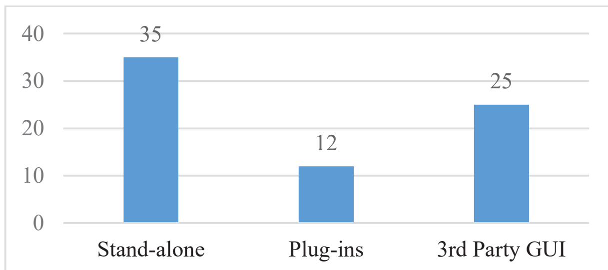

Figure 3: Number of tools with different formats

4.4. Cloud-simulation

The early design stage is usually associated with high iteration frequency when different decisions are assessed and compared. Reliance on conventional simulation hardware which requires long simulation times may then not be a practical solution. Cloud-simulation has allowed for offering real-time feedback as the simulation process is conducted on the cloud rather than on conventional systems, and hence, reducing the processing requirements of computers running the simulation. Cloud-simulation is increasingly being seen as the future by tool-developers, especially those focusing on the early design stages (Attia *et al.*, 2013; Macumber *et al.*, 2014). To underline this, Samuelson et al. (2016) conducted an intensive test running around 90,000 simulations via cloud services within reasonable timing and cost. 18% of the tools such as Green Building Studio were found to adopt cloud-simulation (**Error! Reference source not found.**).

5. Emerging Trends in Building Energy Simulation Application

Review of the emerging trends in development and application of BEPS showed that 66 publications were adopting one or more of these trending methods to assist early design decisions; uncertainty analysis; sensitivity analysis; parametric analysis; genetic algorithms; and artificial neural networks.

5.1. Uncertainty Analysis and Sensitivity Analysis

Early design decisions are usually accompanied by a high level of uncertainty due to lack of data, and a large amount of unknown variables, resulting in uncertainties essential for making confident decisions. This has led to a developing trend in using statistical methods based on Uncertainty Analysis (UA). The role of UA is attempting to quantify the number of uncertainties of different variables to make the decision-making process more reliable through quantifying the simulation results based on the uncertainties of the input variables (Hopfe et al., 2007). UA would aid in giving reliability to the simulation results, which assists the design process when comparing different outcomes.

Table 3 : UA, SA, and PA related studies

#	Study	UA	SA	PA	Source
1	(Anton and TĂnase, 2016)			✓	Anton, I. and TĂnase, D. (2016) 'Informed Geometries: Parametric Modelling and Energy Analysis in Early Stages of Design', Energy Procedia, 85, pp. 9-16.
2	(Banihashemi *et al.*, 2017)			✓	Banihashemi, S., Ding, G. and Wang, J. (2017) 'Developing a hybrid model of prediction and classification algorithms for building energy consumption', Energy Procedia, 110, pp. 371-376.
3	(Berger & Mendes, 2017)		✓		Berger, J. and Mendes, N. (2017) 'An innovative method for the design of high energy performance building envelopes', Applied Energy, 190, pp. 266-277.
4	(Bre *et al.*, 2016)		✓		Bre, F., Silva, A.S., Ghisi, E. and Fachinotti, V.D. (2016) 'Residential building design optimisation using sensitivity analysis and genetic algorithm', Energy and Buildings, 133, pp. 853-866Bre, F., Silva, A.S., Ghisi, E. and Fachinotti, V.D. (2016) 'Residential building design optimisation using sensitivity analysis and genetic algorithm', Energy and Buildings, 133, pp. 853-866.
5	(Burhenne *et al.*, 2013)	✓			Burhenne, S., Tsvetkova, O., Jacob, D., Henze, G.P. and Wagner, A. (2013) 'Uncertainty quantification for combined building performance and cost-benefit analyses', Building and Environment, 62, pp. 143-154.
6	(Delgarm *et al.*, 2018)		✓		Delgarm, N., Sajadi, B., Azarbad, K. and Delgarm, S. (2018) 'Sensitivity analysis of building energy performance: A simulation-based approach using OFAT and variance-based sensitivity analysis methods', Journal of Building Engineering, 15, pp. 181-193.
7	(Elbeltagi *et al.*, 2017)			✓	Elbeltagi, E., Wefki, H., Abdrabou, S., Dawood, M. and Ramzy, A. (2017) 'Visualized strategy for predicting buildings energy consumption during early design stage using parametric analysis', Journal of Building Engineering, 13, pp. 127-136.
8	(Faggianelli *et al.*, 2017)	✓			Faggianelli, G.A., Mora, L. and Merheb, R. (2017) 'Uncertainty quantification for Energy Savings Performance Contracting: Application to an office building', Energy and Buildings, 152, pp. 61-72.
9	(Figueiredo *et al.*, 2016a)		✓		Figueiredo, A., Figueira, J., Vicente, R. and Maio, R. (2016a) 'Thermal comfort and energy performance: Sensitivity analysis to apply the Passive House concept to the Portuguese climate', Building and Environment, 103, pp. 276-288.
10	(Figueiredo *et al.*, 2016b)		✓		Figueiredo, A., Kämpf, J. and Vicente, R. (2016b) 'Passive house optimization for Portugal: Overheating evaluation and energy performance', Energy and Buildings, 118, pp. 181-196.
11	(García *et al.*, 2016)			✓	García Kerdan, I., Raslan, R., Ruyssevelt, P. and Morillón Gálvez, D. (2016) 'An exergoeconomic-based parametric study to examine the effects of active and passive energy retrofit strategies for buildings', Energy and Buildings, 133, pp. 155-171.
12	(Hopfe & Hensen, 2011)	✓			Hopfe, C.J. and Hensen, J.L.M. (2011) 'Uncertainty analysis in building performance simulation for design support', Energy and Buildings, 43(10), pp. 2798-2805.
13	(Jaboyedoff *et al.*, 2015)			✓	Jaboyedoff, P., Cusack, K., Bhanware, P., Ganesan, K., Chetia, S. and Maithel, S. (2015) 14th International Conference of IBPSA - Building Simulation 2015, BS 2015, Conference Proceedings.
14	(Jaffal *et al.*, 2009)			✓	Jaffal, I., Inard, C. and Ghiaus, C. (2009) 'Fast method to predict building heating demand based on the design of experiments', Energy and Buildings, 41(6), pp. 669-677.
15	(Lara *et al.*, 2017)			✓	Lara, R.A., Naboni, E., Pernigotto, G., Cappelletti, F., Zhang, Y., Barzon, F., Gasparella, A. and Romagnoni, P. (2017) Energy Procedia.
16	(Li *et al.*, 2013)			✓	Li, Z., Lin, B., Lv, S. and Peng, B. (2013) Proceedings of BS 2013: 13th Conference of the International Building Performance Simulation Association.
17	(Manfren *et al.*, 2013)	✓			Manfren, M., Aste, N. and Moshksar, R. (2013) 'Calibration and uncertainty analysis for computer models - A meta-model based approach for integrated building energy simulation', Applied Energy, 103, pp. 627-641.
18	(Naboni *et al.*, 2013)			✓	Naboni, E., Zhang, Y., Maccarini, A., Hirsch, E. and Lezzi, D. (2013) Building Simulation Applications.
19	(Nikolaidou *et al.*, 2017)	✓			Nikolaidou, E., Wright, J.A. and Hopfe, C.J. (2017) 'Robust building scheme design optimization for uncertain performance prediction'.
20	(Olofsson *et al.*, 2009)			✓	Olofsson, T., Andersson, S. and Sjögren, J.U. (2009) 'Building energy parameter investigations based on multivariate analysis', Energy and Buildings, 41(1), pp. 71-80.
21	(O'Brien *et al.*, 2011)			✓	O'Brien, W.T., Athienitis, A.K. and Kesik, T. (2011) 'Parametric analysis to support the integrated design and performance modeling of net zero energy houses', ASHRAE Transactions, 117, pp. 945-960.
22	(Østergård *et al.*, 2017a)		✓		Østergård, T., Jensen, R.L. and Maagaard, S.E. (2017a) 'Early Building Design: Informed decision-making by exploring multidimensional design space using sensitivity analysis', Energy and Buildings, 142, pp. 8-22.
23	(Østergård *et al.*, 2017b)		✓		Østergård, T., Jensen, R.L. and Maagaard, S.E. (2017b) 'Interactive Building Design Space Exploration Using Regionalized Sensitivity Analysis', IBPSA.
24	(Pratt and Bosworth, 2011)		✓		B Pratt, K. and E Bosworth, D. (2011) 'A method for the design and analysis of parametric building energy models', Proceedings of Building Simulation 2011: 12th Conference of International Building Performance Simulation Association.
25	(Pudleiner & Colton, 2015)		✓		Pudleiner, D. and Colton, J. (2015) 'Using sensitivity analysis to improve the efficiency of a Net-Zero Energy vaccine warehouse design', Building and Environment, 87, pp. 302-314.
26	(Samuelson *et al.*, 2016)			✓	Samuelson, H., Claussnitzer, S., Goyal, A., Chen, Y. and Romo-Castillo, A. (2016) 'Parametric energy simulation in early design: High-rise residential buildings in urban contexts', Building and Environment, 101, pp. 19-31.
27	(Schlueter et al, 2009)			✓	Schlueter, A. and Thesseling, F. (2009) 'Building information model based energy/exergy performance assessment in early design stages', Automation in construction, 18(2), pp. 153-163.
28	(Schwartz *et al.*, 2017)		✓		Schwartz, Y., Raslan, R., Korolija, I. and Mumovic, D. (2017) 15th International Building Performance Simulation Association Conference, San Francisco, CA, Aug.
29	(Sesana *et al.*, 2011)		✓		Sesana, M.M., Salvalai, G. and Esposito, F. (2011) PLEA 2011 - Architecture and Sustainable Development, Conference Proceedings of the 27th International Conference on Passive and Low Energy Architecture.
30	(Shiel *et al.*, 2018)			✓	Shiel, P., Tarantino, S. and Fischer, M. (2018) 'Parametric analysis of design stage building energy performance simulation models', Energy and Buildings, 172, pp. 78-93.
31	(Singh *et al.*, 2016)	✓	✓		Singh, R., Lazarus, I.J. and Kishore, V.V.N. (2016) 'Uncertainty and sensitivity analyses of energy and visual performances of office building with external venetian blind shading in hot-dry climate', Applied Energy, 184, pp. 155-170.
32	(Spitz *et al.*, 2012)	✓	✓		Spitz, C., Mora, L., Wurtz, E. and Jay, A. (2012) 'Practical application of uncertainty analysis and sensitivity analysis on an experimental house', Energy and Buildings, 55, pp. 459-470.
33	(Suh *et al.*, 2011)			✓	Suh, W.J., Park, C.S. and Kim, D.W. (2011) Proceedings of Building Simulation 2011: 12th Conference of International Building Performance Simulation Association.
34	(Sun *et al.*, 2015)	✓			Sun, Y., Huang, P. and Huang, G. (2015) 'A multi-criteria system design optimization for net zero energy buildings under uncertainties', Energy and Buildings, 97, pp. 196-204.
35	(Wang & Zhao, 2018)		✓		Wang, Z. and Zhao, J. (2018) 'Optimization of Passive Envelop Energy Efficient Measures for Office Buildings in Different Climate Regions of China Based on Modified Sensitivity Analysis', Sustainability, 10(4), p. 907.
36	(Xu *et al.*, 2017)			✓	Xu, W., Lam, K. and Karaguzel, O. (2017) 15th International IBPSA Conference.
37	(Xu *et al.*, 2018)			✓	Xu, X., Feng, G., Chi, D., Liu, M. and Dou, B. (2018) 'Optimization of performance parameter design and energy use prediction for nearly zero energy buildings', Energies, 11(12).
38	(Yan *et al.*, 2017)	✓		✓	Yan, B., Li, X., Shi, W., Zhang, X. and Malkawi, A. (2017) 'Forecasting Building Energy Demand under Uncertainty Using Gaussian Process Regression: Feature Selection, Baseline Prediction, Parametric Analysis and a Web-based Tool', IBPSA.
39	(Yang *et al.*, 2016)		✓		Yang, S., Tian, W., Cubi, E., Meng, Q., Liu, Y. and Wei, L. (2016) 'Comparison of Sensitivity Analysis Methods in Building Energy Assessment', Procedia Engineering, 146, pp. 174-181.

9 studies of the 66 were found to adopt the UA (Table 3). Another common trend in research is Sensitivity Analysis (SA). SA is applied to comprehend relationships between building parameters. The basic concept is that the building's performance could be enhanced when adjusting the values of the different parameters in relation to each other (Nguyen and Reiter, 2015). SA could be described as a measure of the effect of a certain input on the resulting output in relation to building performance (Saltelli et al., 2004). Hemsath and Bandhosseini (2015) advocate that applying SA at the early design stage would lead to better identification of the parameters with the highest impact on the building performance, and hence assists in reaching better decisions. 16 studies adopted SA (Table 3).

5.2. Parametric Analysis

Another trending method is parametric analysis (PA). PA tests the effects of changes on either one or more building parameters in relation to other parameters related to building efficiency using coordinated formulas (Suyoto et al., 2015). PA is usually performed via visual programming methods, and commonly used in conjunction with UA and SA where one of the main applications is in the field of building energy performance optimisation (Anderson and Tang, 2011). PA is evident in 8 of the 64 listed design tools as an extra feature (**Error! Reference source not found.**). And was used in 21 of the listed studies in Table 3.

5.3. Building Optimisation

Building optimisation (BO) is not a field, but recent novel and emerging methods are being developed to assist early design applications. BO is based on running a number of computational algorithms in order to reach optimal parameter-combinations for the building design (Machairas *et al.*, 2014; Saeed, 2017). BO methods are usually used in energy performance-based design approaches. Despite increasing research in BO, applications remain scarce in practice (Citherlet, 2001). There is believed to be a number of challenges that hinder wider uptake, namely; the process is time-consuming; requires high computational powers; and a high level of expertise.

5.4. Artificial intelligence

The applications of artificial intelligence (AI) in the field of energy prediction and optimisation theory is gaining increasing trust regarding calibrating the optimum parameter permutations in an automated manner (Engelbrecht, 2007). Examples of AI methods are Genetic Algorithms (GA) and Artificial Neural Networks (ANN) which are based on mimicking biological systems by applying a number of algorithms in order to perform different tasks. GA is mainly based on the concept of evolving genetics. It is processed through producing a number of generations with specific parameters. Each generation is simulated and tested in relation to a pre-defined efficiency margin. Optimised parameters are then kept while other parameters are enhanced in a following generation. The process continues until a near-optimal solution is reached (Sha et al., 2019). 24 of the 66 studies adopted GA (Table 4).

ANN imitates the functions of neural networks through simulating arithmetic computational models (Saeed, 2017). To predict the energy performance through a machine learning process, the ANN model consists of a number of nodes where each simulates an equation. The nodes are connected through a network to allow for non-linear calculations. The machine learning process exposes the model to a range of historical simulation results based on a number of input parameters, where on each round, the model is informed that a certain input is expected to provide a certain output (Nguyen et al., 2014). The process is repeated until the nodes have formulated suitable equations that would produce similar results to those produced by other simulation software. Another way is to teach the model real-world input parameters from existing buildings, together with the actual consumption. This assists in reducing the performance gap between simulated and actual readings (Machairas et al., 2014). Although the machine learning process demands very large amount of data and time, the resulting models give faster results compared to conventional simulation. 12 studies in the list were found to use ANN (Table 4).

Among the 64 tools, only EnergyElephant and cove.tool were found to be AI supported (**Error! Reference source not found.**).

Table 4: GA and ANN related studies

#	Study	GA	ANN	Source
1	(Ascione *et al.*, 2016)	✓		Ascione, F., De Masi, R.F., de Rossi, F., Ruggiero, S. and Vanoli, G.P. (2016) 'Optimization of building envelope design for nZEBs in Mediterranean climate: Performance analysis of residential case study', Applied Energy, 183, pp. 938-957.
2	(Ascione *et al.*, 2017)		✓	Ascione, F., Bianco, N., De Stasio, C., Mauro, G.M. and Vanoli, G.P. (2017) 'Artificial neural networks to predict energy performance and retrofit scenarios for any member of a building category: A novel approach', Energy, 118, pp. 999-1017.
3	(Azari *et al.*, 2016)	✓	✓	Azari, R., Garshasbi, S., Amini, P., Rashed-Ali, H. and Mohammadi, Y. (2016) 'Multi-objective optimization of building envelope design for life cycle environmental performance', Energy and Buildings, 126, pp. 524-534.
4	(Banihashemi *et al.*, 2017)		✓	Banihashemi, S., Ding, G. and Wang, J. (2017) 'Developing a hybrid model of prediction and classification algorithms for building energy consumption', Energy Procedia, 110, pp. 371-376.
5	(Bogar *et al.*, 2013)	✓		Bogar, D., Rapone, G., Mahdavi, A. and Saro, O. (2013) Building Simulation Applications.
6	(Bre and Fachinotti, 2017)	✓		Bre, F. and Fachinotti, V.D. (2017) 'A computational multi-objective optimization method to improve energy efficiency and thermal comfort in dwellings', Energy and Buildings, 154, pp. 283-294.
7	(Bre *et al.*, 2016)	✓		Bre, F., Silva, A.S., Ghisi, E. and Fachinotti, V.D. (2016) 'Residential building design optimisation using sensitivity analysis and genetic algorithm', Energy and Buildings, 133, pp. 853-866
8	(Calcerano et al, 2016)	✓		Calcerano, F. and Martinelli, L. (2016) 'Numerical optimisation through dynamic simulation of the position of trees around a stand-alone building to reduce cooling energy consumption', Energy and Buildings, 112, pp. 234-243.
9	(Carlucci *et al.*, 2015)	✓		Carlucci, S., Cattarin, G., Causone, F. and Pagliano, L. (2015) 'Multi-objective optimization of a nearly zero-energy building based on thermal and visual discomfort minimization using a non-dominated sorting genetic algorithm (NSGA-II)', Energy and Buildings, 104, pp. 378-394.
10	(Chen *et al.*, 2018)	✓		Chen, X., Yang, H. and Zhang, W. (2018) 'Simulation-based approach to optimize passively designed buildings: A case study on a typical architectural form in hot and humid climates', Renewable and Sustainable Energy Reviews, 82, pp. 1712-1725.
11	(Dan and Phuc, 2018)		✓	Dan, T.X. and Phuc, P.N.K. (2018) Proceedings 2018 4th International Conference on Green Technology and Sustainable Development, GTSD 2018.
12	(Delgarm *et al.*, 2016b)	✓		Delgarm, N., Sajadi, B., Delgarm, S. and Kowsary, F. (2016) 'A novel approach for the simulation-based optimization of the buildings energy consumption using NSGA-II: Case study in Iran', Energy and Buildings, 127, pp. 552-560.
13	(Dong *et al.*, 2017)		✓	Dong, Q., Xing, K. and Zhang, H. (2017) 'Artificial neural network for assessment of energy consumption and cost for cross laminated timber office building in severe cold regions', Sustainability, 10(1), p. 84.
14	(Fang and Cho, 2017)	✓		Fang, Y. and Cho, S. (2017) 'Building Geometry Optimization with Integrated Daylighting and Energy Simulation', IBPSA.
15	(Ferrara et al., 2018)	✓		Ferrara, M., Sirombo, E. and Fabrizio, E. (2018) 'Automated optimization for the integrated design process: the energy, thermal and visual comfort nexus', Energy and Buildings, 168, pp. 413-427.
16	(Geyer and Schlüter, 2014)	✓		Geyer, P. and Schlüter, A. (2014) 'Automated metamodel generation for Design Space Exploration and decision-making - A novel method supporting performance-oriented building design and retrofitting', Applied Energy, 119, pp. 537-556.
17	(Gossard *et al.*, 2013)	✓	✓	Gossard, D., Lartigue, B. and Thellier, F. (2013) 'Multi-objective optimization of a building envelope for thermal performance using genetic algorithms and artificial neural network', Energy and Buildings, 67, pp. 253-260.
18	(Harkouss *et al.*, 2018)	✓		Harkouss, F., Fardoun, F. and Biwole, P.H. (2018) 'Multi-objective optimization methodology for net zero energy buildings', Journal of Building Engineering, 16, pp. 57-71.
19	(Kumar *et al.*, 2018)		✓	Kumar, S., Pal, S.K. and Singh, R.P. (2018) 'A novel method based on extreme learning machine to predict heating and cooling load through design and structural attributes', Energy and Buildings, 176, pp. 275-286.
20	(Lara *et al.*, 2017)	✓		Lara, R.A., Naboni, E., Pernigotto, G., Cappelletti, F., Zhang, Y., Barzon, F., Gasparella, A. and Romagnoni, P. (2017) Energy Procedia.
21	(Li *et al.*, 2018)	✓		Li, Z., Chen, H., Lin, B. and Zhu, Y. (2018) 'Fast bidirectional building performance optimization at the early design stage', Building Simulation, 11(4), pp. 647-661.
22	(Melo *et al.*, 2017)		✓	Melo, A.P., Lamberts, R., Cóstola, D. and Hensen, J.L. (2017) 'Development of a method to predict building energy consumption through an artificial neural network approach', IBPSA.
23	(Ngo, 2019)		✓	Ngo, N.T. (2019) 'Early predicting cooling loads for energy-efficient design in office buildings by machine learning', Energy and Buildings, 182, pp. 264-273.
24	(Polson *et al.*, 2017)	✓		Polson, D., Zacharis, E., Lawrie, O. and Vagiou, D. (2017) 'Multi-Objective Optimisation In Early Stage Design. Case Study: Northampton University Creative Hub Building', IBPSA.
25	(Powers, 2017)	✓		Powers, A. (2017) 'A Modified Genetic Optimization Algorithm Using Ancestor Path Extrapolation', IBPSA.
26	(Santos *et al.*, 2017)	✓		Santos, L., Schleicher, S. and Caldas, L. (2017) 'Automation of CAD models to BEM models for performance based goal-oriented design methods', Building and Environment, 112, pp. 144-158.
27	(Shi, 2011)	✓		Shi, X. (2011) 'Design optimization of insulation usage and space conditioning load using energy simulation and genetic algorithm', Energy, 36(3), pp. 1659-1667.
28	(Tuhus & Krarti, 2010)	✓		Tuhus-Dubrow, D. and Krarti, M. (2010) 'Genetic-algorithm based approach to optimize building envelope design for residential buildings', Building and Environment, 45(7), pp. 1574-1581.
29	(Xu *et al.*, 2018)		✓	Xu, X., Feng, G., Chi, D., Liu, M. and Dou, B. (2018) 'Optimization of performance parameter design and energy use prediction for nearly zero energy buildings', Energies, 11(12).
30	(Yi and Malkawi, 2009)	✓		Yi, Y.K. and Malkawi, A.M. (2009) 'Optimizing building form for energy performance based on hierarchical geometry relation', Automation in Construction, 18(6), pp. 825-833.
31	(Zhang *et al.*, 2017)	✓		Zhang, A., Bokel, R., van den Dobbelsteen, A., Sun, Y., Huang, Q. and Zhang, Q. (2017) 'Optimization of thermal and daylight performance of school buildings based on a multi-objective genetic algorithm in the cold climate of China', Energy and Buildings, 139, pp. 371-384.

6. Discussion and Conclusion

This study is part of a wider PhD research on the use of BEPS tools in informing architectural decisions in the early design stages. The study covered twofold objective of the larger research aim through establishing the state of the art in energy modelling tools, to define a categorization and identify recent and emerging trends in their development and application in practice in the last decade (between 2008 and 2019). The methodology adopted a semi-inductive approach, however, the review was framed and limited in accordance with architectural decision-making assistance at the early design stages. The research methodology covered an investigation for the currently available BEPS tools where hundreds of tools were filtered to meet set criteria; 55 tools were found in practice, in addition to 9 in research. Those were then analysed and categorized according to certain development aspects. In terms of targeted user groups, only four tools were found to be mainly targeting architects, while 55% of the tools were aiming to target both architects and engineers. 46% of the listed tools were developed to be used at the conceptual design stage, while the remaining 53% were created to be used for verification purposes later on in the design stage and hence have minimal impact on earlier decisions. BEPS tools were found to have been used in three tool formats with; 55% of the tools to be stand-alone with their own calculation engines; 12 tools provided a plug-in option in other design authoring tools such as Revit, Sketchup, and Rhinoceros to facilitate informing architectural design decisions at early stages and in relation to high design frequency iteration at the early stages, some tools have developed solutions such as the cloud-based simulation to offer real-time results for testing what-if-scenarios instantly. Cloud-simulation was found to be provided by 12 tools.

Regarding the emerging trends in BEPS methods, a filtration process was applied to 730 systematically reviewed publications. 66 publications were then critically reviewed and were found to adopt one or more of the discussed trending methods. As a response to the high level of uncertainty usually accompanied with early design decisions; statistical methods such as sensitivity and uncertainty analysis were found to be trending within 22 publications to quantify the uncertainty level and to calculate the effect different parameters calibration would have on the building's performance. Also for early design decisions making, parametric analysis method was present within 18 publications. The method is usually offered via visual programming platforms where the results of parameter value variations could be visually analysed. In practice, 8 of the listed tools are providing the PA option. Other trending methods for energy performance prediction and building optimization at early stages were found to be AI assisted. Mimicking biological neural networks, ANN would assist in reaching quite accurate energy predictions via machine learning methods through exposure to historical building parameters and their subsequent resulted energy performance. The method is promising in regards to decreasing the performance gap between conventionally simulated and actual results. The main issue is that a lot of data is needed for the calculation model to develop, however once developed, instant results could be calculated. Another AI method is GA mimicking the idea of natural selection to reach an optimized set of parameters through a number of generations. ANN and GA were found to be adopted by 31 studies. Despite being a trend in academia, however, among the 66 tools, only Energy Elephant and cove. Tool were found to be AI assisted.

Emerging trends in the development and application of BEPS in practice are showing increasing concern for aiding early design decisions. This is shown in the increasing number of tools and methods developed for use at the early stage, and tools developed to accommodate architects' requirements. The need for quick and accurate feedback have allowed for new simulation methods as cloud-simulation to emerge. Also, plug-in tools within design authoring tools have increased. Future research shall dig into practice in the UK context to measure the impact of such tools and methods on the ground.

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