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Building simulations supporting decision making in early design – A review

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The building design community is challenged by continuously increasing energy demands, which are often combined with ambitious goals for indoor environment, for environmental impact, and for building costs. To aid decision-making, building simulation is widely used in the late design stages, but its application is still limited in the early stages in which design decisions have a major impact on final building performance and costs. The early integration of simulation software faces several challenges, which include time-consuming modeling, rapid change of the design, conflicting requirements, input uncertainties, and large design variability. In addition, building design is a multi-collaborator discipline, where design decisions are influenced by architects, engineers, contractors, and building owners. This review covers developments in both academia and in commercial software industry that target these challenges. Identified research areas include statistical methods, optimisation, proactive simulations, knowledge based input generation, and interoperability between CAD-software and building performance software. Based on promising developments in literature, we propose a simulation framework that facilitates proactive, intelligent, and experience based building simulation which aid decision making in early design. To find software candidates accommodating this framework, we compare existing software with regard to intended usage, interoperability, complexity, objectives, and ability to perform various parametric simulations.

Keywords: Building performance, uncertainty analysis, sensitivity analysis, interoperability, optimisation, knowledge based input generation

Abbreviations: building performance simulation (BPS), one-at-a-time (OAT), uncertainty analysis (UA), sensitivity analysis (SA), life cycle costs (LCC), life cycle analysis (LCA)

1 Introduction

The building design community is challenged by continuously increasing energy demands which are often in conjunction with ambitious goals for the indoor environment. The recast of the European Performance of Buildings Directive (EPBD) requires all new buildings in the European Union to be "nearly zero energy" buildings by 2020 [1]. In addition to stricter energy demands, the use of environmental assessment methods has increased considerably [2][3]. As a result, the design team must try to optimize on a large number of criteria, such as energy demand, indoor environment, materials, life cycle cost, etc., which are often conflicting. Supporting decision making and guiding the design towards high performance is of utmost importance in the early design phase where decisions have the highest impact on final performance and costs [4][5][6] [1]. Predicting the consequences of early decisions is particularly difficult, but crucial, since adverse decisions will reduce the remaining design space and make it more strenuous and expensive to meet high performance goals. For example, the design team may early on decide on a design concept with a highly transparent facade favoring daylight (high window-to-wall-ratio) where potential issues, concerning cooling energy, thermal comfort, and glare, are avoided by a combination of hybrid ventilation and automatic, external shading. If the initial conditions later turn out to be too optimistic or unrealistic (e.g. solar shading in use more that 80% of the time, venting needs an air change of more than 10 h^{-1} to keep temperatures within limits), it will have major impact on both cost and design to remedy this early decision and reach ambitious goals. Despite the potential of performing building simulations, the information obtained from building performance simulation software is often evaluative instead of proactive [5][7]. Even when the software is sophisticated, accurate, and capable of assessing a wide range of different performance indicators, it is often most suitable for code compliance, benchmarking, and quality control. There is a lack of tools that provide timely feedback on performance implications and help compare and rank multiple design variations [8][5]. The software's ability to provide this kind of active support is sometimes referred to as "intelligence" [5][9]. In a survey among 230 architects, "intelligence" and "usability" ranked higher than "interoperability" and "accuracy" when selecting BPS tools [5]. In other words, the software's ability to inform and guide the design has the highest priority by the majority of the architects. According to Batueva and Mahdavi [9], less than 8 percent of more than 400 building simulations tools listed by the U.S. Department of Energy [10] have potential for early design deployment potential. In summary, challenges of performing building simulations at the early stages, identified by the authors, include: lack of information, uncertainty, vast design space, increasing levels of model resolution (level of detail), time-consuming modeling, and rapid change of design. In general, challenges affecting all stages of building design include: contradicting and stricter requirements, interoperability, limited reuse of knowledge, discrepancy between simulations and real-life measurements, and lack of simulation guidance.

The main focus of this review is to identify state-of-the-art within the field of building simulations addressing the challenges above. The review is part of a research project which aims to develop a simulation framework that addresses all of these diverse challenges in order to facilitate proactive, intelligent, and experience based building simulations. Another ambition of the research is to implement such a framework in the design project as early as possible. Below, we outline six research areas targeting at least one of the identified challenges, and we specify how this review differs from previous reviews related to building simulations. In chapter 2, we describe

[1] In this review, we distinguish between early design and detailed design. In addition, the early design stage may be split into two phases: conceptual design, in which the building concept is developed and schematic drawings are produced; and preliminary design, where schematic drawings are refined to estimate the main quantities for the building project (adopted from [11]).

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how each of the six research areas approaches the issues of BPS, and we highlight promising and trending methods. In chapter 3, we propose an ideal framework for building performance simulations based on our findings in chapter 2. In continuation of this, we carry out a software review in search for available software that fits the requirements and properties of this “ideal” framework.

In this paper, attention is drawn to developments facilitating improved assistance and guidance for the design team during the early design stages. Particular interest is given to methods that enable the designer to investigate a global design space, which is expanded from the variability of multiple design parameters. The reason for this is that a single building performance simulation only evaluates a single point in the design space without taking uncertainties and variability into account. Nor does the single evaluation guide the designer on how to improve the design. As a consequence, designers often perform manual or automatic, parametric simulations varying one parameter at a time. This one-at-a-time approach (OAT) is referred to as local analysis. In early design, many parameters may be varied at the same time which advocates exploration of a global design space, which presumable can reveal higher performing design as illustrated on Figure 1.

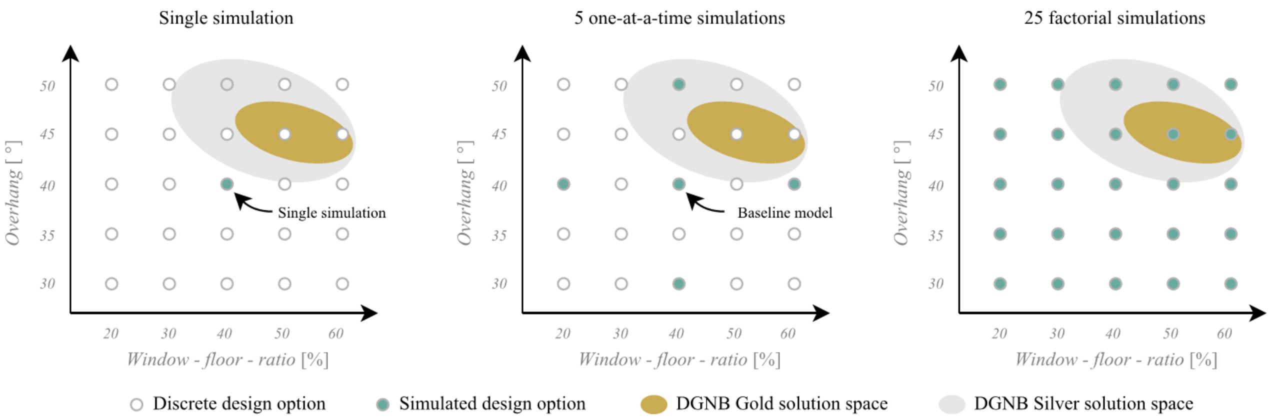


Figure 1 Different explorations of a 2D discretized design space. Favorable solution spaces are illustrated by simulations resulting in best (Gold) and second best (Silver) awards according to the DGNB certification system for sustainable buildings [11] (similar to e.g. LEED Platinum and Gold certification [12])

1.1 Research targeting early building simulations

This review covers a wide range of research addressing the challenges related to building simulations as identified above. To create an overview, the reviewed papers have been organized into six larger groups of research areas – each of them targeting one or more specific challenges as illustrated on Figure 2. Definitions of these intertwined research areas, and motive for their inclusion, are as follows:

- Proactive building simulations refer to a proactive exploration of the design space in order to guide the design rather than evaluate design.
- Statistical methods include running large numbers of simulations and applying statistical measures. As well as coping with uncertainties, a statistical approach may facilitate exploration of a large design space and identify important inputs and favorable input domains.
- Holistic design includes calculation of many interdependent performance objectives and combining the results to support decision making. Examples of important interdependent objectives are energy demand, thermal comfort, and daylight.
- Optimisation on performance objectives helps to automate the exploration of a large design space and guide the design towards high performance.
- CAD-BPS interoperability may be achieved by integration of models, run-time coupling, and shared schemas. A common ambition is to ensure fast and consistent modeling.
- Knowledge based methods aim to reuse and share knowledge to reduce the time spent modeling, and they seek to improve consistency and validity. Moreover, knowledge databases may be used to set default values to enable simulations when the input resolution is low (model detail).

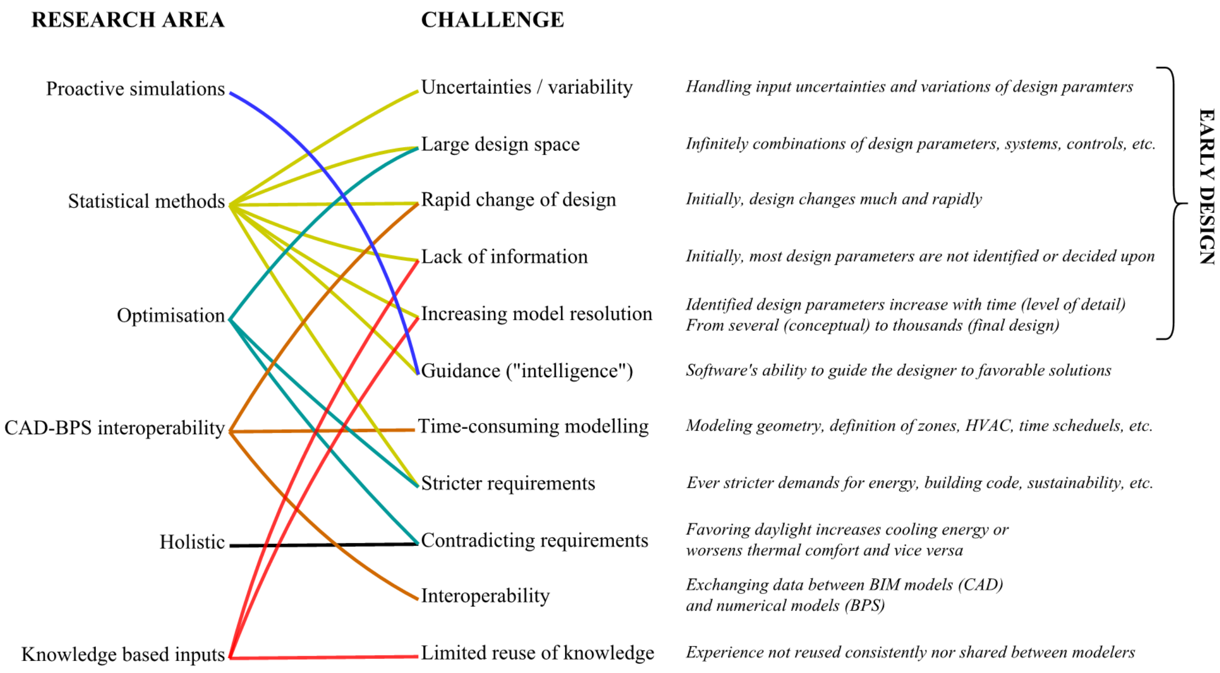


Figure 2 The reviewed research areas and their relation to different challenges of performing building simulations in the early design stages and in general.

Since the main focus of the review is simulations made in the early design phases, we will not cover efforts in improved algorithms describing building physics. Nor will we address methods which primarily intend to improve detailed analysis or reduce performance gaps.

1.2 Literature reviews and comparative surveys

Prior to this study, we found a considerable amount of comparative studies and reviews concerning building performance simulations. These studies provide a comprehensive insight into a specific discipline or branch of building design, such as: energy simulation, daylight simulation, software comparison, optimisation, sensitivity analysis, etc. This review covers a more wide range of research areas to see how the industry might benefit from the combined efforts made across disciplines. The reader looking for a more in-depth review of a specific topic may look into the following:

- Kanters et al. [8]: Tools and methods used by architects for solar design
- Hopfe et al. [13]: Comparison of 6 BPS tools and potential of BPS in conceptual design phase
- Crawley et al. [14]: Comparison of 20 building energy performance simulation programs
- Attia et al. [15]: Survey with 249 architects and their relation to 10 BPS tools
- Attia and Herde [16]: Comparison of 10 early design simulation tools
- Zhao et al. [17]: Review on the prediction of building energy consumption
- Pacheco et al. [18]: Review on energy efficient design of building
- Ochoa et al. [19]: Review of lighting simulation for building science
- Tian [20]: Review of sensitivity analysis methods in building energy analysis
- Evins [21]: Review of computational optimization methods applied to sustainable building design
- Machairas et al. [22]: Review of algorithms for optimization of building design
- Bucking et al. [23]: Uncertainty, sensitivity, and optimisation in building simulation
- Iwaro et al. [24]: Criteria weighting framework and multi-criteria decision making
- Fumo [25]: Basics and classification of whole building energy estimations

Primarily works after 2005 have been included.

2 Research areas

2.1 *Proactive building simulations*

The engineer responsible for building performance simulations regarding energy, comfort, cost, etc., are often asked various “What if…” questions by building owners, entrepreneurs, and architects. These questions refer to alternative design options, such as “what if we allow external shading”, “what if we increase window-to-wall ratio”, “what if we combine venting and overhangs to avoid mechanical cooling”. Since most simulation software is evaluative in nature, such queries are difficult to give immediate replies to – especially in the early design phase where the option space is immense. Trying to answer such queries will often require the simulation expert to run additionally simulations between meetings or workshops. When the answers are obtained, it may already be too late, since the design has evolved and new issues and questions have arisen instead. Addressing this issue of time-consuming, iterative, and evaluative nature of building simulation, Shady et al. [5] used the concept of “pre-design informative” BPS that enables proactive guidance and support for decision making during early design. According to the authors, only 1 % of the then 392 tools listed on the U.S. Department of Energy homepage [26] can be categorized as pre-design informative.

In this paper, we will distinguish between the terms “pre-design informative” and “proactive” simulations. The term “pre-design informative” is applied to methods where simulations have been carried out prior to the design stage. Examples include the constructions of meta-models (see section 2.2.3) and the creation of databases from simulations of predefined rooms or building types. “Proactive” is considered a more broad term that also applies to methods where alternative simulations are carried out in a structured way to guide, rather than evaluate, the design.

Petersen [7] recognizes the potential of the simulation environment to become more proactive and provide data-driven advice along with design implications. He therefore focuses on enabling “the support environment to generate input to the overall building design process prior to any actual design decisions”. Petersen introduces a novel tool that enables parametric, room-level simulations with respect to energy consumption, air quality, daylight, and thermal comfort. For all inputs, the user assigns a reference value and optionally two alternative values. Along with the reference model, the tool will then perform one-at-a-time simulations to evaluate two variations for each of the varied parameters. The tool was tested on three real building projects, where the actors involved found this one-at-the-time parametric analysis useful for decision support. Though, the extent to which the design information was allowed to influence design decision differed due to different opinions on the benefits from interdisciplinary collaboration in the conceptual design stage. This demonstrates the importance of an open mind towards multi-actor collaboration and towards the implementation of novel methods and tools that may improve the design process.

Similar to Petersen’s approach, Ochoa and Capeluto [27] have developed an advice tool for the conceptual design stage of intelligent facades based on energy and visual comfort. The tool employs the EnergyPlus [28] engine in order to evaluate intelligent facades and to ensure continuity with the subsequent preliminary and detailed design phases. The many EnergyPlus inputs are abstracted away by using presets that are determined from a few architectural considerations concerning location, main orientation, occupancy level, sophistication level, facade openness, surroundings, and building depth. In that way, the architect does not need to assign specific input values into the simulation tool. Instead, the designer defines relatively few properties regarding geometry and location along with some desired design concepts. On the basis of these properties and design intentions, the tool creates building design alternatives that follow a set of built-in design rules. An interesting feature is that the logic also generates an alternative with a degree of randomness to avoid locking the designer into one direction. In the end, the designer is presented with a list of detailed design alternatives.

Attia et al. [5] has developed a prototype tool for net zero-energy buildings in hot climates with the purpose to inform designers prior to decision making. The prototype consists of a simple and easy-to-use interface enabling parametric runs of the EnergyPlus simulation engine. Numerous inputs for EnergyPlus have been reduced to reflect the early design stage. This allows for fast creation and exploration of a variety of alternatives while using advanced, validated simulation software. The prototype allows for simulation of a number of predefined building types and applies sensitivity analysis to guide decision making.

The above works focus on early design integration, creation of alternatives, and guidance of the designer. Such ambitions may also be facilitated by means of statistical methods as described in the following section.

2.2 *Statistical methods*

In this context, statistical methods refers to a design process where the modeler runs a large number of simulations in a structured manner and use statistical techniques to achieve design support from the simulated data. This approach enables the modeler to explore a large design space in a systematic way, which potentially enlarges the solution space, and thereby improves building performance compared to typical one-at-a-time parametric analysis (see Figure 1). Statistical analysis also allows for definition of inputs in form of possible spans, thereby addressing the issue of non-determined or uncertain inputs that is characteristic of the early design phase. Finally, statistical analyses are suitable for addressing the challenges related to the probabilistic nature of user behavior and weather.

Statistical building performance modeling consists of three intertwined disciplines, namely uncertainty analysis, sensitivity analysis, and multivariate analysis. Present work covers diverse uses of statistical analysis, but the following steps are common (see reduced workflow on Figure 3):

1. A baseline model is created in building performance software capable of calculating the objectives of interest.
2. Depending on the scope of the analysis, a number of input parameters, ranging from a few to hundreds, are selected. Each parameter is assigned with a probability density function that reflects parameter uncertainty related to the numerical model, boundary condition, physical property, or design variability.
3. A sample matrix is constructed from the probability density functions. Various sampling procedures exist and their applicability depends on the analysis to be performed. Sampling procedures include random, stratified, factorial, Latin hybercube, and quasi-random with low-discrepancy sequences [29].
4. For each sample a building simulation is performed and outputs of interest are collected.
5. Results are analyzed utilizing uncertainty analysis, sensitivity analysis, multivariate analysis, or combinations of these. The results may also be used to create meta-models as described below.

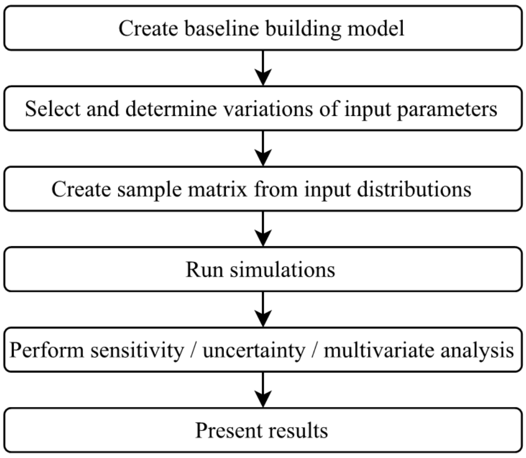


Figure 3 Schematic flow diagram of typical implementation of statistical analyses in a building performance simulation process.

This workflow is often facilitated by using statistical software packages such as SimLab [30] or the statistical programming language R [31] in combination with building performance software [20][32]. Increasing interest and need for such workflows drives developers to create extensions to the building simulation environment to facilitate parametric modelling, e.g. Parametric Analysis Tool for OpenStudio [33] and jEPlus [34]. It seems that the proliferation of scripting languages, particularly interpreted and dynamically typed languages such as Python and Ruby, makes programming more accessible for simulation specialists who want to perform very specific simulation tasks [35][36][37].

2.2.1 Uncertainty Analysis

An early, comprehensive research of uncertainties related to building simulations was conducted by MacDonald [38], who addressed the problem of quantifying the effects of uncertainties on the predictions derived from building simulation software. More recent work focus on utilizing uncertainty analysis as part of the decision making process [39][40][41][42]. Hopfe and Hensen [41] conclude that "the integration of uncertainties in BPS provides evidence based decision support in design team meetings and dialogues with building partners." When augmented by sensitivity analysis such integration will give an idea of the significance of uncertainties and facilitate quality assurance of the model. Uncertainty analysis is useful to investigate design variation and gives insight into design robustness and possible ranges of performance indicators, i.e. minimum and maximum values for energy demand, daylight metrics, costs, etc. However, decision making under consideration of uncertainty is not straightforward. As exemplified by de Wit and Augenbroe [39] a decision maker will find it difficult to decide whether or not to implement a cooling system when such a system is required if the hours with overheating exceeds 150 but the overheating temperatures are represented by a probability functions that spans over this limit. To address this issue, the authors propose implementation of Bayesian decision theory by setting up and comparing utility functions. Another approach for decision-making under uncertainty is suggested by Rezaee et al. [42]. They estimate the level of confidence that option *A* performs better than option *B* by comparing output distributions for each of the two alternatives. Thereby, the designer gets an idea of how likely it is that one design proposal will outperform another.

Since uncertainty is inherent in all building simulations one might argue always to include uncertainty analysis. Even in late retrofit design and in model calibration, the effects of occupants' behavior and unpredictable weather impose substantial uncertainty on the model's predictions which militate against use of deterministic calculations. Various studies applied uncertainty and sensitivity analysis to study the effects of occupants' behavior and weather variability [43][44][45][46][47] [48]. Brohus et al. [43] perform both a theoretical and empirical study of energy consumption of domestic buildings which shows occupant's behavior to be the major contributor to the variance. Hoes et al. [44] also include thermal analysis in an office case study and propose a methodology for better representation of user behavior. Their results show that no general design concept ensures robustness towards user behavior without applying extensive oversized active systems. According to O'Brien [45], implementation of passive systems, e.g. fixed solar shading, may reduce both energy use and uncertainty associated with occupant behavior. Applying uncertainty analysis is often accomplished by assigning probability density distributions to uncertain inputs as described above. This method, however, does not work for uncertainties related to user behavior and weather when performing whole-year simulations. To address this issue, Rodríquez et al. [46] defines three levels of both occupant load and weather load. By combining these, a total of nine scenarios are investigated which enhances the robustness of the analysis. Furthermore, the authors apply sensitivity analysis which shows that the ranking of influential inputs are similar for the nine investigated scenarios.

Summing up, uncertainty analysis may aid building design in various manners. This analysis ensures more reliability to the results, enables exploration of large design spaces, and assesses model quality and robustness. Though, design comparison becomes less straightforward when considering uncertainties as compared to evaluating deterministic calculations.

2.2.2 Sensitivity Analysis

Various authors suggest to incorporate sensitivity analysis during early design to identify the input parameters with highest impact on building performance [40][49] [50][51][52]. By identifying the most influential input parameters, the design team may direct their attention to these inputs in subsequent analyses, such as parameter variations and optimisation, and during construction of meta-models. Sensitivity analysis may answer "What-if" questions by calculating regression or correlation coefficients which indicate the size and direction of the change in performance when changing values for a certain input [40][53]. Different sensitivity analysis techniques are described thoroughly in an often cited book "Global Sensitivity Analysis: The Primer" by Saltelli et al. [29], while the use of sensitivity analysis in building energy analysis is covered in a comprehensive review by Tian [20].

Sensitivity analysis can be divided into local and global approaches [29]. Derivative based local methods consider the effects of uncertain inputs around a point in design space (or baseline model) by varying one parameter at a time (OAT). This approach requires few computations but is ill-suited for non-linear systems [29]. Global methods consider the uncertain inputs over the whole input space. Global methods are more versatile since they can handle nonlinear, non-additive, and non-monotone systems and consider the effects of interactions between inputs. As an example of a nonlinear and non-monotone system in BPS, we may consider energy consumption as a function of windows' g-value. For a given model, the heating load in winter may be reduced by increasing the g-value but only to a certain limit after which the cooling load will increase. Yet, this relationship is highly dependent on other parameters such as fenestration, solar shading, shadows, set points, internal loads, etc. These complex relations may be investigated by applying sophisticated, global sensitivity analysis methods such as decomposition of variance and other quantitative measure. Though, these approaches typically increase the amount of computational effort accordingly. Hemsath and Bandhosseini [52] argue that pre-design local sensitivity coefficients may aid early decision-making, and it may be extended to global analysis in a later design optimisation stage.

Sensitivity analysis may be applied for multiple performance indicators and thereby provide an overview of critical design parameters in a holistic design context. Using an office test case, Jin and Overend [53] calculated sensitivity indices for 14 facade design variables with respect to 13 different outputs related to energy, comfort, and cost. The resulting sensitivity coefficient charts for three different climatic zones help allocate design time and construction budget to the variables with highest impact on performance.

2.2.3 Meta-modelling

A meta-model may be defined as a simplified model of a model. In other words, if a numerical model is an abstraction of the real world, the meta-model is yet another abstraction of that numerical model. Meta-modelling involves analysis of input and output relationships in order to establish a mathematical relationship (algorithm) that is easy and fast to compute. A broad range of techniques exist, such as Artificial Neural Network (ANN) [54], Support Vector Machines (SVM) [55], Kriging [56], Multivariate Linear Regression [4], [57], but in general no type is optimal in all circumstances [58].

In a building simulation context, a meta-model is typically constructed from a large set of simulations made with validated, detailed building performance software which is often computationally heavy. Alternatively, a meta-model may be constructed from experimental or observational data. For instance, meta-models can be constructed from large building performance databases [56][59]. The simplified model usually consists of a limited set of inputs and outputs that are relevant for the task at hand. The reduced set of inputs and the computationally fast algorithms makes meta-modelling attractive for early building design where only a few variables have been identified and the demand for fast feedback is crucial. Due to the fast algorithms, meta-modelling may be attractive when performing optimisation, uncertainty analysis, sensitivity analysis, and real-time simulations. Techniques based on regression analysis, sometimes considered easier and more practical [60], enable both interpretation and prediction [61]. Interpretation of regression coefficient helps understand input-output relationships as well as interactions between inputs – i.e. sensitivity analysis is easily accomplished. Additionally, regression coefficients enable prediction of building performance and hence provide proactive decision support.

The literature, reviewed here, concerns early building design, retrofit analysis, and test of the meta-modeling techniques. Performance indicators of interest include heating and cooling loads [4], [55]–[57], [62], [63], thermal comfort [55], indoor air quality [54], daylight factor [60] and net cost [62]. The training set for establishing the models consist of both experimental [56], [59] and simulated data. The use of meta-modelling in a holistic context will probably become highly laborious since individual algorithms must be developed for each performance indicator. Furthermore, a meta-model is only applicable in the domain of which it has been constructed, i.e. it becomes invalid if the prerequisites change, e.g. loads, orientation, constructions, etc. This characteristic is a considerable downside worth mentioning.

2.2.4 Multivariate analysis and Filtering

Several authors make use of a stochastic approach to run an exhaustive set of simulations of the design space [33][51][64]. Applying filtering methods afterwards help identify favorable areas of the design space that meet certain design criteria [32]. Moreover, multivariate analysis of the vast amount of data obtained from thousands of simulations may be assisted by various visualization techniques such as scatterplots, histograms, and parallel coordinate plots. Naboni et al. [64] demonstrate the possibilities of cloud computing by running 221.184 EnergyPlus [28] simulations within 72 hours. Using factorial sampling of 8 discrete design variables, all combinations are considered. The method is compared to a conventional manual approach where a practitioner is assumed to generate and run up to 50 manually configured simulations. When comparing time consumption, the additional computational time of the parametric approach is balanced out by the time spent on setting up and analyzing the manual simulations. The advantage of the parametric modelling is the exhaustive, global investigation of the design space and the possibility to apply statistical analysis. By comparing Pareto fronts, the authors show that the parametric approach may reduce both cooling and heating needs significantly. For instance, the energy savings are increased by 33 % when choosing the best performing parametric design as comparing to the best performing manually configured design.

2.3 Holistic Design

A building design needs to satisfy a vast range of often contradicting requirements and objectives. Certification schemes such as DGNB [11], LEED [12], and BREEAM [65] involve evaluation of up to 100 objectives. Some may be estimated quantitatively with simulation software while others can only be evaluated qualitatively. Another characteristic of the building design process is the gradually increase in identified design parameters and objectives [40]. For example, it is nearly impossible to calculate room acoustics, draught, and LCA in conceptual design. Since objectives are often correlated, a design change improving a certain objective will affect other objectives as well. These circumstances challenge the holistic design approach, especially in the early design phase. As stated by Cheung et al. [35] "There is a clear need for a designer-focused system that can give simultaneous design assessment on various aspects in the conceptual design stage."

One element of holistic design in a simulation context is to enable simultaneous calculations of as many objectives as possible. This may be facilitated by improved interoperability by common file exchange schemas (IFC, gbXML, etc.) or by integrating a multitude of algorithms into one software platform (see section 2.5). Another element is to combine these diverse performance results and extract information that supports decision making. This lies in the extensive field of multi-criteria decision making (MCDM).

Pohekar & Ramachandran [66] and Wang et al. [67] have made reviews on MCDM in neighboring research areas and describe different techniques that aid decision making when considering conflicting and multiple objectives. These methods are based on weighting averages, priority setting (Analytical Hierarchy Process (AHP)), outranking (ELECTRE, PROMETHEE), and fuzzy principles [66][67]. In the field of sustainable energy decision-making, the simple method of equal criteria weights are the most popular followed by the more comprehensive Analytical Hierarchy Process [67]. Similar trends may apply to the field of building design, where weighting systems is demonstrated by Bjørn and Brohus [68], Iwaro et al. [69], and Østergård et al. [24]. Moreover, weighting frameworks, such as DGNB, LEED, and BREEAM, are getting increasingly popular. These weighting systems involve prioritization and establishment of comparable performance measures. Such systems compel the design team to think holistic and they reveal which objectives may be improved.

In the Analytical Hierarchy Process the decision problem is decomposed into a hierarchy of sub-problems. Decision makers compare these sub-problems pairwise by assigning numbers from 1 as 'equally important' up to e.g. 9 for 'extremely more important' [70]. A matrix consisting of all pairwise comparisons is used to calculate numerical weights for all objectives in the hierarchy, allowing diverse objectives to be compared in a consistent way. Hopfe et al. [70] use AHP to support multi-criteria decision making under uncertainty based on stakeholders preferences. By propagating uncertainty from design parameters into probability distributions of performance indicators, much information is generated but it complicates decision making (see example in section 2.2). Applying AHP helps rank design options where uncertainty is included and thereby aids decision making while reaping the benefits from uncertainty analysis. According to Iwaro et al. [24], the majority of the subjective criteria weighting frameworks, such as AHP, fail to consider objective information. Therefore, Iwaro et al. suggest an integrated frame where AHP is combined with an objective weighting approach to assess life cycle performance. The framework was concluded to provide a robust methodology for weighting and assessment of the sustainable performance of residential building designs.

Another research dealing with uncertainties and multiple objectives is that of Jin and Overend [53]. As described in section 2.2, the authors take into account the large uncertainties related to early design to create façade sensitivity charts for 13 output variables describing the performance of two office scenarios in three geographical locations.

Holistic design promotes evaluation of a vast number of opposing performance indicators. Since design comparison becomes more troublesome when considering multiple objectives, the design team may want to exclude objectives having little importance or having large correlation with other objectives. An example of the latter, in a Danish context, is the evaluation of overheating hours above 26 °C and 27 °C, which are required by building code. From a design perspective, the two measures will show similar behavior and addressing either one of them will most likely have similar consequences on building design. These nearly redundant objectives may be excluded to reduce the information load. To identify such objectives, the following methods are listed by Wang et al. [67]: the least mean square method, the min-max deviation method, and the correlation coefficient method. These methods are simple to apply and may help to focus on the most important parameters in a holistic design process.

In this brief overview of holistic design, we have left out multi-criteria optimisation which will be covered in the following. In holistic design, we stress that optimisation requires caution since building design is a high-dimensional and complex task where a single best holistic solution (or single Pareto front) does not exists.

2.4 Optimisation

In this context, optimisation refers to the automated use of mathematical optimisation in combination with building performance simulations. The aim of this section is to give an overview of trends, benefits, and challenges based on five reviews [21], [22], [71]–[73] related to building design optimisation. A building optimisation analysis typically consists of the following steps that may be repeated in an iterative design process (combined from Machairas [22] and Nguyen et al. [72]):

1. Identification of design variables and constraints
2. Selection of simulation tool and creation of a baseline model
3. Selection of objective function(s)
4. Selection of optimisation algorithm
5. Running simulations until optimisation convergence is achieved
6. Interpretation and presentation of data

Since the turn of the millennia, publications about building optimisation have roughly increased tenfold [21][22][72]. This development is aided by advances in computer science in terms of parallel and cloud computing as well as advancements in optimisation theory where genetic algorithms (GA) and particle swarm optimisation are prevalent [71][72]. Based on keyword searches in the scientific database “ScienceDirect”, Machairas et al. [22] conclude that optimisation on HVAC and controls represent the majority of the publications. Though, optimisation of parameters influencing building design has become increasingly popular during the last decade. Applying optimisation to building design is often motivated by the stringent and often divergent requirements of high-performance buildings. Interviews with researchers and practitioners emphasize that optimisation of building design is not about finding the “best” solution but rather to find alternative solutions from automated exploration of a large design space [71]. Arguably, “parameter variations” may be a better term when this is the purpose of the optimisation.

Building designers seek to design buildings that perform well on a wide range of both quantitative and qualitative measures. While early building optimisation studies were dominantly single objective, the trend is towards multi-objective optimisation [21]. One way to include more objectives is to apply the weighted-sum method which reduces the optimisation problem to single-objective at the cost of introducing arbitrary fixed weights to all objectives. Otherwise, multi-objective optimisation consists of quantifying trade-offs curves of solutions, known as Pareto Fronts, where objectives cannot be improved further without worsening others. Typically, multi-optimisation addresses only two objectives though a few recent works applied full 3-objective optimisation [74][75].

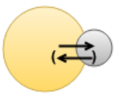
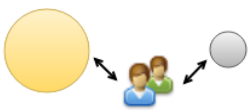
According to two different reviews [21][76], the common objectives to optimize, in decreasing order, are energy, cost, thermal comfort, and carbon dioxide. Often, optimisation of one or two objectives is performed while setting constraints for other objectives to make sure the constrained objectives comply with relevant standards. Arguably, this approach is inadequate when the designer needs to score high in holistic assessments such as LEED [12], BREEAM [65], and DGNB [11] where the overall score depends on a wide range of opposing objectives. In such cases, the weighted sum method seems more appropriate. Furthermore, since building simulations lack qualitative measures, such as aesthetics, space layout, and logistics, optimisation on a few objectives may be at the cost of equally important qualitative measures.

Despite the growing interest for building performance optimisation in academia, adoption in practice is still limited [71]. Barriers to widespread implementation consist of various issues that need be addressed. Time-consuming computations have long been a well-known obstacle. This may be overcome by the proliferation of parallel and cloud computing or by constructing computationally fast meta-models [21]. Another issue is the inability of optimisation algorithms to cope with uncertainties [21], which are especially large for early building design. Performing optimisation is not trivial, and it requires knowledge and experience to formulate the problem properly and select appropriate software and algorithms which calls for education of practitioners [71]. Another hurdle is that available optimisation tools, either generic[2] or customized for building simulations[3], require time-consuming and error-prone linking to the simulation software [71]. A solution for this could be full integration of optimisation techniques into commercial software. In addition, interviewed researchers and practitioners desired the following features: better GUIs, parallel computing, and coupling of simulation software and optimisation tools to do real-time optimisation within BIM models [71]. Simulation experts also need to prove legibility of optimisation to architects, building owners, and contractors since building design is a multi-collaborative iterative process where stakeholders have different areas of responsibility.

2.5 CAD-BPS interoperability

For many years, the field of data exchange and interoperability between CAD models and building performance simulations (BPS) has received a lot of attention among software developers and researchers. Table 1 illustrates different ways of combining CAD and BPS, i.e. representations of the physical world (CAD) and analytical, numerical models (BPS). Note that the illustrations in Table 1 only show one numerical model although there often exists a number of such models of varying sizes. Moreover, interoperability may be a mix of the methods shown. For example, run-time interoperability often only works when there exists a common file exchange format. Furthermore, one type of analysis may be performed using an integrated, simplified algorithm for early design support, whereas a more detailed analysis might prove necessary in later stages. For example, detailed simulations using CFD software.

Table 1 Characteristics and examples of four different methods to combine CAD (large disk) and BPS (small disk). Categorization adopted from Petersen [7] and Citherlet [77]

Method		Characteristics	Examples
Integrated		Numerical calculations integrated into CAD environment.	Collision control, duct sizing, and solar analysis
Run-time interoperable		Links between CAD software and analytical models established by add-on or API. Simulations performed at run-time or in a concurrently running desktop or web edition of the BPS tool.	Grasshopper and Dynamo plugins. SketchUp & Revit with Sefaira, OpenStudio
File exchange		Common file exchange format readable and sometimes writable from both CAD and BPS tools – i.e. Building Information Modelling (BIM).	Proprietary: dwg, rvt, gbXML, osm Public: IFC, XML
Standalone (users interpret)		Data interpreted by users. Building simulationist remodels building or selected rooms by interpreting CAD models or drawings and eventually presents results orally or in reports.	EnergyPlus, Radiance

[2] E.g. GenOpt, ModelCenter, modeFRONTIER, DAKOTA, iSIGHT, Matlab optimisation toolbox [136]
[3] E.g. BEopt, TRNOPT, MultiOpt, jEPlus + EA, GENE-ARCH, Opt-E-Plus [136]

2.5.1 Integration and direct links in early design

Improved interoperability would address several of the early design issues identified in the introduction, e.g. time-consuming iterative modelling, and need for rapid feedback. Since the early design stages are dominated by architects, who create building models using CAD software, this section focus on the features of the integrated and run-time coupled approaches.

During the last decades, the CAD industry has evolved from 2D drawings to 3D models and now "4D" models where more and more semantic data is integrated into the CAD environment. Moreover, advanced CAD software tends to integrate an increasingly amount of analyses, such as collision control, duct sizing, and solar analysis. In addition, various software vendors facilitate BPS through dynamically coupled tools or add-ons. Examples include Autodesk's Green Building Studio [78] for Revit [79] while Graphisoft's has EcoDesigner Star [80] for ArchiCAD [81]. Third party vendors also enable direct links to BPS through application programming interfaces (API) to promote early design decision support and rapid analyses. These include Sefaira [82], IESVE [83], and OpenStudio [84] that may be linked to SketchUp [85]. Several of these couplings rely on common file formats to do so, i.e. IFC, gbXML, osm, etc. Various plug-ins and API's make use of detailed software engines, such as EnergyPlus [28], Daysim [86], and Radiance [87], which are computationally heavy and require lots of inputs. As a consequence, most inputs are assigned to defaults values related to specific building types. The challenge of running time-consuming BPS, while designing in CAD, may be overcome by applying cloud computing. Such development may facilitate run-time analysis, enable rapid feedback, ease iterations, and reduce amount of (re)modeling. Moreover, zoning may be set up in the CAD environment after which changes in geometry automatically updates zoning as well. To test such an integrated framework, Batueva and Mahdavi [9] assessed the use of Graphisoft's EcoDesigner [80] which has been integrated into ArchiCAD. The authors acknowledge the effortless interoperability but desire more intelligence in terms of guidance and comparison features [9].

Much of these efforts rely on software vendors to incorporate BPS into the CAD domain, or link the two, but similar work is carried out in the scientific community [88]–[92]. Jakubiec and Reinhart [89] describe a plugin for Rhinoceros [93] which combines daylight analysis, using Radiance and Daysim, with thermal load calculations, using EnergyPlus. Muehleisen and Craig [90] implement the ISO 13790 monthly energy model into the OpenStudio environment, which is available as a plug-in for SketchUp. The authors conclude that this particular plug-in is suitable for parametric simulations and Monte Carlo analysis during early design, because the simulation time is five orders magnitude faster than the equivalent EnergyPlus model and the simplified algorithm requires far fewer inputs.

2.5.2 Parametric geometric modelling

As exemplified by various authors [94][95][96], parametric modeling are increasingly adopted in design practice by means of tools like Grasshopper [97], Dynamo [98], and GenerativeComponents [99]. Concurrently, plug-ins are developed to link these tools with BPS thereby enabling data-driven support for early stage, parametric, and geometric modeling. Examples of plug-ins for the probably most widely used tool, Grasshopper, include: a) Honeybee which links to Radiance, Daysim, EnergyPlus, and Openstudio [100]; b) Mr. Comfy which facilitate interactive visualizations of thermal simulations results [91]; c) ICEbear that integrates indoor climate, daylight, and energy performance [92]; and d) Tortuga [101] which estimates LCA and a global warning potential based on the Ökobau database [102]. Comprehensive libraries of applications relevant to the architecture, engineering, and construction industries can be found on the sites aec-apps.com [103] and Food4Rhino [104]. The ability to add several plug-ins to parametric modeling could be a feasible way to facilitate holistic simulation support. Though, even if plug-ins ensure smooth CAD-BPS interoperability during the early design phases such plug-ins may not be suitable for detailed analysis. Therefore, it is desirable that plug-ins make use of detailed software engines or common exchange formats to avoid complete remodeling, and to avoid inconsistent results, when the design evolves to detailed stages.

Despite improvements with interoperability, plenty obstacles remain. Most of the couplings illustrated by arrows in Table 1 are uni-directional. It is very seldom that properties derived from BPS are transferred back to architectural or BIM model. Moreover, BIM are still challenged by the complexity of the heterogeneous BPS data which requires user interpretation as well as extensive pre-processing and enrichment of incomplete building information [105][106]. Moreover, this central framework with a shared schema has to be operated in consensus with all stakeholders, i.e. architects, engineers, and contractors [107]. Aforementioned examples of coupled and integrated models are often limited to single user use, since the coupled programs normally have to be installed on the same computer. This is troublesome in a multi-actor, interdisciplinary collaboration where different actors possess expertise and responsibility over different areas [105].

In conclusion, much effort is made in academia and by software developers to improve interoperability between CAD and BPS in the early design stages. Achieving effortless interoperability and smooth transition between design stages will make life easier for all parties involved.

2.6 Knowledge based input generation

Building performance software requires hundreds or thousands of inputs which may be assigned manually by the user or by importing data from CAD models, shared schemas (BIM), and databases within the software. Databases may include constructions, HVAC components, load and user profiles, weather data, etc. They play an important role in terms of modelling time and reliability. The quality and applicability of such databases depend on their ability to address several issues such as:

- Ease of implementation
- Scalability and updatable
- "Best practice", i.e. in accordance with code compliance or prior experience
- Flexibility, e.g. usable for both early and detailed analysis and across different tools
- Ability to be varied in multiple (parametric, batch, or stochastic) simulations
- Documentation and validity

Vendor supplied libraries often serve as the only or main source of information for practitioners and are often poorly documented and difficult to share and reuse across applications [106]. Such issues are addressed by National Renewable Energy Laboratory that are developing a comprehensive, online, searchable library of energy building blocks and descriptive metadata which works for different applications [108] [109], e.g. EnergyPlus [28], OpenStudio [84], and DOE2 [110]. Flexible and extensible set of attributes provide the opportunity to add metadata such as U-value, cost, and images. In addition, the attributes "user ratings" and "number of downloads" may support the selection of materials, components, and systems across fields and practitioners.

Another large online database is the "building performance database" which contains information about physical and operational characteristics of hundreds of thousands of real commercial and residential buildings in the U.S. [26][111]. Aimed at the vast retrofit market, this database enables assessment of energy retrofitting opportunities and helps to quantify risk related to project performance. A statistics tool is integrated to estimate expected changes in energy performance due to changes in component technologies. Though, since the database primarily concerns energy from existing buildings, the effects on indoor climate performance resulting from retrofitting remain unknown.

Performing simulations in the early design phase is challenged by lack of data. This is especially the case for detailed simulation software that requires a high level of information. This difficulty may be overcome by a macro-component approach where pre-defined constructions allows for energy and LCA assessments in the early phase using detailed software [112]. Similarly, Rodríguez et al. [46] aggregates macro-parameters of occupancy and weather data to enable uncertainty and sensitivity analysis in detailed models. Hiyama et al. [113] propose a method to automatically generate default configuration for simulations in the early stage thereby making the design process more efficient and consistent. The configurations are based on past experience in combination with objectives and constraints of the current project.

Pont et al. [114] make use of semantic web technologies to acquire and utilize building related data available on the Internet. Semantic rules and reasoning enable restructuring of ill-structured "web of documents" to machine-readable "web of data" by means of interlinking data from various web sources and by re-categorizing the data using consistent logic. Such methods can in theory be applied to any web-based resources such as databases and manufacturer sites. Data from different sources may be merged into one rich library with links to original data and providing opportunity for regular updates and acquisition of new information. This could be information about construction types, materials' properties, and prices,

The increasing use of uncertainty analysis and sensitivity analysis calls for development of databases that facilitate stochastic simulations. In contrast to deterministic defaults, the designer needs recommendations in terms of appropriate input distributions, input spans, and sampling strategies. Lee et al. [115] present an uncertainty and risk analysis toolkit that give energy modelers access to previously defined uncertainty distributions for a variety of parameters and models. Furthermore, the toolkit provides automatic identification and modification of parameters values in simulation input files. Such efforts might make uncertainty analysis more accessible for non-specialists and help to increase the use of UA and SA.

To sum up, databases may be employed in a variety of ways to support and improve the building design process. When used for setting up initial configurations for building simulations, the practitioner must be aware of certain inherent risks: a) the configuration may return results in local "optimum" causing the designer to stop exploring a sufficiently large design space, b) default configuration may lead to misleading baseline models if there is a big discrepancy between database values and measurements, new requirements, and codes, c) initial configurations used in architectural design software may guide the architect in wrong directions if these configurations are not aligned with engineers who are responsible for code compliance in detailed design phase.

3 Software comparison

As stated in the introduction, the motivation for this review is to identify state-of-the-art within the field of building simulations with emphasis on early design. In chapter 2, we covered developments in literature across six research areas. In this chapter, we will propose a simulation framework combining the most promising methods found in literature after which we compare existing software packages that may satisfy some of the requirements of such a framework.

In the introduction, we identified a number of challenges related to building simulations in the design process (see Figure 2). To address these diverse issues, it is necessary to combine several of the methods and developments described in the literature review in chapter 2. Based on those findings, we describe a framework that, presumably, facilitates proactive, intelligent, and experience based building simulation which aid decision making in early design. The proposed framework contains the following properties, which are combined in an iterative design process as illustrated on Figure 3:

0. A knowledge based database represents the starting and finishing point for each project. It must facilitate fast input generation, consistency, and collection of experience. Moreover, the database should contain macro-parameters to enable the use of detailed software in early design stages (macro-parameters represent predefined sets of constructions, HVAC systems, time schedules, etc. that contain the input values necessary to run a detailed simulation). Finally, it should ease the definition of uncertain inputs.
1. A baseline model is swiftly set up by a combination of database inputs and suitable CAD interoperability.
2. Uncertainties are assigned to inputs and a sampling strategy is applied to explore the global design space and to facilitate uncertainty and sensitivity analysis
3. Thousands of simulations are run using a validated and detailed software engine(s) that evaluate important, interdependent design objectives.
4. Data is analyzed using UA and SA.
5. On the basis of UA and SA, attention is drawn to the most important design parameters and the design team is informed of benefits and consequences of various design strategies. Interactive visualization allows for interaction with the simulated data where different stakeholders preferences may be explored.

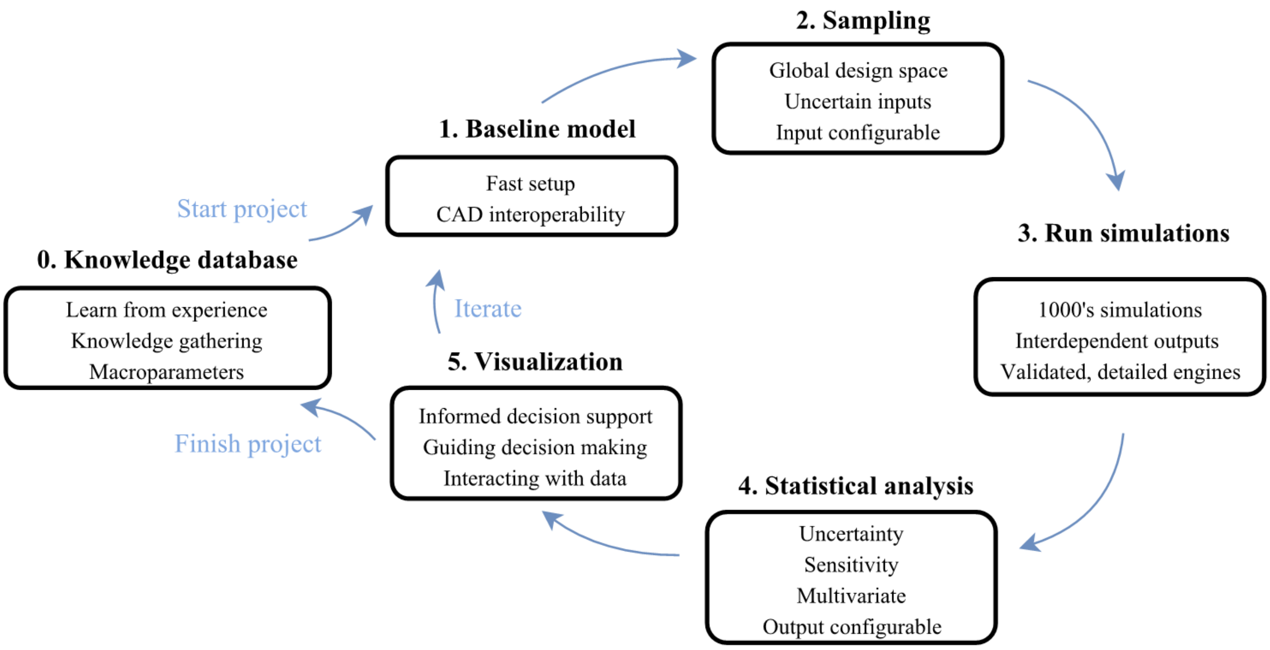


Figure 4 Desired workflow and properties as facilitated by the proposed simulation framework.

The properties of desired framework shown on Figure 4 entail various requirements of the simulation software. Therefore, we carry out a software review to assess features and limitations of current building simulations software packages. If no software satisfies all requirements, we aim to find software candidates that may be combined into the desired framework. Important properties of the reviewed software are[4]:

- **A. Users:** Is the software primarily intended for architects, engineers, or both?
- **B. Design stage:** In which design stages are the software typically used?

[4] Properties, omitted in this work, include: licensing, price, version, status (beta, deprecated), and number of users/downloads.

C. Interoperability: How does the BPS software connect to CAD environment and other software packages (see Table 1 for definitions)?

D. Level of complexity of the core algorithms: The complexity set the constraints of design options that the software enables to investigate and to what level of detail. For energy and thermal calculations, the monthly averaged ISO 13790 [116] is considered to have a “low” complexity level, as opposed to detailed software with “high” level of complexity due to features like multi-zones, advanced fenestration, HVAC and lighting control strategies, moisture transport, etc. Somewhere in between, we have the hourly averaged ISO 13790 [116] and RC models. For daylight calculations, simplified regression models have “low” complexity compared to advanced algorithms that, for instance, use ray tracing or radiosity to evaluate illuminance, luminance, and glare under various sky conditions and at different times a year [19].

E. Objectives: Important, interdependent objectives must be evaluated to ensure holistic design.

F. Parametric: Ability to run global parametric calculations and to perform UA and SA – either by using integrated features or by configuring input text files and accessing output text files. Option to enable cloud computing is desirable.

In the search for relevant, existing software, we rely on various resources: the tools directory list on U.S. department of energy homepage [10], the AEC-apps homepage [103], the BLDG-SIM mailing list [117], and prior knowledge of novel and trending software in Scandinavia. A reduced set of programs have been selected for further investigation. Deprecated software packages (Ecotect, Vasari) have been excluded along with software that did not seem to fit into the proposed framework (Modelica and TrnSys). The selected programs differ greatly in scope, validation, purpose, price, level of detail, and more, but each of them can potentially fulfill a specific purpose in the framework described in Figure 4. Table 2 shows how the software compares. In the evaluation of the software, we rely on vendors’ homepages, webinars, manuals, colleagues, and other reviews from academia [8][14][118][119]. Readers are reminded that both table structure and table inputs are very much governed by our subjective perceptions of the programs’ capabilities.

Table 2 Comparison of software in terms of fulfilling the requirements of the proposed software framework. Checkmarks indicate fulfilment of the requirement. Checkmarks in parenthesis indicate that software include the specific feature without satisfying the requirement. See explanations of headers A to F in the text.

	Software	A. Users	B. Design stage				C. Interoperability	D. Core complexity	E. Objectives						F. Parametric sim.						Ref.
			Conceptual	Preliminary	Detailed	Management			Energy	Thermal	Daylight	Air Quality	LCA	LCC	Cloud	I/O Configurable	UA	SA	OAT	Optimisation	
BPS (own engine)	Be10 (ISO 13790 monthly)[2]	(A)E		—			Standalone	Low	✓	(✓)						✓					[120]
	Bsim	E		—	—		Standalone	High	✓	✓	✓	✓							(✓)		[121]
	DOE2	E			—		Standalone	Medium	✓							✓					[110]
	EnergyPlus (E+)	E			—		Standalone	High	✓	✓		✓				✓					[28]
	EPC (ISO 13790 hourly)	(A)E	—	—			Standalone	Medium								✓					[122]
	ESP-r	E			—		Standalone	High	✓	✓		✓				✓					[123]
	IDA-ICE	E		—	—		File exchange	High	✓	✓		✓				✓			✓		[124]
	iDbuild	E	—	—	—		Standalone	Medium	✓	✓	✓	✓							✓		[125]
	IESVE	E		—	—		File exchange	High	✓	✓	✓	✓	✓	✓							[83]
	Radiance	E		—	—		Standalone	High			✓					✓					[87]
	VELUX Daylight Visualizer	AE	—	—	—		File exchange	High			✓										[126]
BPS (external engine)	A+E3D	A	—	—			Integrated	Be10	✓	(✓)	(✓)										[127]
	Daysim	E	—	—	—		Run-time	Radiance			✓										[86]
	DesignBuilder	E		—	—		File exchange	E+, Radiance	✓	✓	✓	✓		✓						✓	[128]
	eQuest	E		—	—		Standalone	DOE2	✓												[129]
	N++	E	—	—	—		Separated	E+, jE+, GenOpt	✓	✓		✓							✓	✓	[130]
	OpenStudio	E		—	—	—	File exchange	E+, Radiance	✓	✓	✓	✓		✓	✓	✓					[84]
	Riuska	E		—	—		File exchange	DOE 2, own engine	✓	✓		✓					✓	✓			[131]
	Sefaira	A	—	—			Run-time	E+, Radiance	✓	✓	✓				✓		(✓)	(✓)		✓	[82]
Plug-in	DIVA for Rhino	A(E)	—	—	—		Run-time	Radiance			✓										[132]
	Green Building Studio	A(E)	—	—			File exchange	DOE2	✓						✓						[78]
	HoneyBee (GH)	AE	—	—	—		File exchange	OpenStudio, E+, Radiance	✓	✓	✓			✓		✓					[100]
	jEPlus (+ JESS)	E		—	—		Run-time	E+, DesignBuilder, N++	✓	✓	✓	✓		✓	✓		(✓)	(✓)	✓		[133]
	Parametric Analysis Tool	E		—	—		File exchange	OpenStudio	✓	✓	✓	✓		✓	✓		✓	✓	✓	✓	[134]
	Solon	(A)E		—	—		File exchange	Green Building Studio	✓						✓			(✓)	✓		[135]
Glue[1]	Dynamo	AE	—	—			-	-													[98]
	Grasshopper (GH)	AE	—	—			-	-													[97]

[1] Glue refers to software that enable links between BPS and geometrical modeling through graphical programming (also refered to as algorithmic modeling)

[2] Be10 is mandaroty to use for code compliance in Denmark

According to our limited review, no existing software package satisfies all requirements of the proposed framework described Figure 4. Though, the following three software setups may be used as starting point to test the framework.

Riuska [131] has integrated UA and SA into a standalone application which removes the challenges of linking the processes “sampling” and “statistical analysis” with the execution of the simulations (the links illustrated by arrows between 2 and 3, and 3 and 4 on Figure 4). Supposedly, the lack of several important objectives (daylight, LCA, LCC) will be difficult to remedy by combining Riuska with other applications since UA and SA are constrained to Riuska.

OpenStudio [84] is a collection of software tools which include the validated, detailed applications EnergyPlus and Radiance. The packages “parametric analysis tool” (PAT) and “large scale analysis” extends OpenStudio’s capabilities by enabling large parametric studies and cloud computing. A SketchUp plug-in facilitate use in early design whereas gbXML compatibility allows for geometry import from e.g. detailed Revit [79] CAD models for the late design stage. Through a SketchUp plug-in, OpenStudio may access the online, searchable library of user-rated building blocks described in section 2.6 [108] and thereby include several features of the desired knowledge-based database. The combined set of tools seems to contain most of the properties needed by the proposed framework. Though, several features are still under development (beta-versions) and the use of all the packages mentioned (PAT, online database, large scale analysis, and SketchUp plugin) may be precarious and error-prone.

Honeybee [100] connects the Grasshopper and Rhino framework with OpenStudio and thereby combines the strengths of these packages. The former enables parametric studies of building geometry while the link to OpenStudio allows for building performance evaluation. However, Honeybee cannot access all features of OpenStudio – namely the “parametric analysis tool” and the “large scale analysis. A possible drawback is that the Rhino software is often not detailed enough for the final design models, which complicates data interoperability in the transition from preliminary to detailed design.

In conclusion, it is still not possible to perform global and holistic UA and SA that simultaneously vary geometry, zoning, materials, and systems. Riuska seems like a suitable fit for the engineer who wants to learn about, and experiment with, global parameter variations with emphasis on energy and thermal comfort. The OpenStudio framework expands these possibilities even further by accessing a knowledge based database, assessing most performance metrics, and enabling cloud computing. Though, obstacles remain in order to combine these capacities with the parametric tools, Dynamo and Grasshopper, which are growing increasingly popular among architects in particular. We emphasize that geometric parameter variations should be done while varying other sensitive inputs as well, i.e. global variations (see Figure 1). Otherwise, the results from the BPS will only be valid around the specific baseline with fixed HVAC system, controls, materials, etc.

4 Conclusion and discussion

This paper provides an overview of the developments in academia and in the software industry related to the use of building simulations in early building design. As identified in the introduction, challenges to early stage deployment include lack of information, uncertainties, model resolution, and rapid change of design. In addition, general challenges include interoperability, time-consuming modeling, stricter and opposing requirements, limited reuse of knowledge, and simulation guidance. We identified six areas of research addressing one or more of these challenges: proactive building simulations, statistical methods, holistic design, optimisation, CAD-BPS interoperability, and knowledge based input generation. Below, we describe promising developments within these research areas along with our perception of how these developments may be used to improve building simulation in the early stages.

Proactive building simulations

Building simulation software is typically used to ensure building code compliance or to evaluate the performance of a few alternative designs or systems. Therefore, most software lacks the ability to guide the designer towards better performing buildings. To remedy this, a few authors have developed design tools to perform proactive building simulations. The three prototypes, reviewed here [5][7][27], allow fast creation of a number of alternative designs with emphasis on the early design phase. Such efforts contrast the typical, time-consuming trial-and-error approach. To avoid locking the designer in one direction, one tool [27] included a degree of randomness into the logic creating design alternatives.

Statistical methods

In academia, there is a growing interest in stochastic simulations supported by statistical analysis. This approach enables the design team to handle uncertainties and to explore large design spaces. Several works apply sensitivity analysis to identify correlations and interdependencies between inputs, and to rank design inputs of importance [49][50][52] . Other works uses parametric simulations or building performance databases [56][59]to construct fast meta-models which have few inputs and are suitable for rapid simulations. However, meta-models are only valid in the domains in which they were constructed. Applying uncertainty analysis are shown to add reliability to results, help explore vast design spaces [41], and assess model quality and robustness [44][45] (e.g. against uncertainties related to user behavior and weather [46]). Though, the inclusion of uncertainties makes design comparisons less straightforward. Finally, multivariate analysis and filtering techniques are effective when analyzing large dissect large amount of simulation data to guide decision makers [51][64].

Holistic design

The need to address multiple, contradicting objectives emphasizes a holistic approach during all stages of the design process. The means to do so are diverse and include weighted scoring systems [68][69], improved CAD-BPS interoperability, analytical hierarchy processes [24][70], and sensitivity charts of multiple objectives [53].

Optimisation

Motivated by the stringent and often divergent requirements of high performance buildings, optimisation algorithms have become increasingly popular in academia over the last ten years. The trend is towards multi-objective algorithms which focus on energy, cost, thermal comfort, and CO_2 [21][76]. However, algorithms are still limited to two or three variables at a time. A more important drawback is that optimisation lacks qualitative measures such as aesthetics, space layout, and logistics, which are critical parameters in early design. Thus, optimisation may favor solutions that come at the cost of other equally important qualitative measures.

CAD-BPS interoperability

For decades, academia and software developers have given much attention to the interoperability between CAD and BPS. These efforts address the issues of time-consuming modeling, continuity, and interdisciplinary collaboration. The different approaches to CAD-BPS interoperability may be split into four categories: a) integrated, b) run-time interoperable, c) file exchange, and d) standalone. Dominant vendors gradually integrate algorithms directly into the CAD software [80], or they develop proprietary BPS software to ease interoperability [78]. Concurrently, a wide range of add-on applications come to life in academia and in open-source communities. Much attention is put on run-time coupling to ensure fast feedback and enable parametric analysis [82][100]. The field is rapidly evolving, but still needs to overcome difficult obstacles (for instance, project configuration changes from one project to the next, and project members rely on different software packages and modeling tradition). An important challenge is the multi-actor collaboration in building design where companies team up differently for each project and have different software tools and design approaches.

Knowledge based input generation

Input generation for building simulation is often time-consuming and lacks reusability of best practice. Vendor supplied input databases are often rigid and have been made for detailed simulations in the late design stages. The works reviewed here cover “the development of flexible, online database with optional user ratings” [108][109]; “the definition of macro-components for level of detail in early design” [112]; and “input generation using semantic web technologies” [114]. However, the use of default inputs may limit the exploration of the design space since default configurations act as constraints for possible solutions. Further work is needed to improve input databases to account for the vast possibilities in early design and to enable stochastic modelling.

Based on the literature review, we have proposed a simulation framework with the ambition to facilitate proactive, intelligent, and experience based building simulations (see Figure 4). Though applicable during all design stages, emphasis is on assisting the design team to explore the vast design space in the early phases. Another essential element, of the framework, is to ensure holistic design thinking in order to create buildings with high overall performance and with respect to different stakeholders’ preferences. The proposed framework incorporates promising methods and ideas from literature, among others: flexible and experience based database for consistency and fast setup; uncertainty and sensitivity analysis to explore design space and ensure robustness; and a holistic approach considering multiple, contradicting objectives (e.g. energy, thermal comfort, and daylight). Finally, the proposed exploration of a vast, global design space using thousands of detailed simulations requires cloud computing to ensure sufficiently fast response time in the early phases.

We may test the framework hypothetically using the example from the introduction, in which a highly transparent design is justified by a combination of venting and solar shading with unrealistic preconditions. First of all, sophisticated (detailed) algorithms are needed to model venting and shading systems appropriately. Secondly, a holistic approach ensures that emphasis on certain objectives, such as daylight and transparency, does not come at the expense of other important objectives, like energy and thermal comfort. Uncertainty analysis may reveal insufficient robustness towards uncertainties related to control strategy, user behavior, and weather. Sensitivity analysis can help the designer to identify the most important simulation inputs, on which he can direct his attention. And finally, a knowledge based database would reduce the risk of starting out with unrealistically inputs.

To identify potential software satisfying the properties of the proposed framework, we have compared 27 software packages, plug-ins, and environments (see Table 2). From these, we highlighted three different setups, consisting of the standalone software Riuska [131], the OpenStudio framework [84], and the plugin Honeybee [100] that links Grasshopper [97] and OpenStudio. Since, currently these tools do not satisfy all requirements of the framework, further research and development is needed to enable setups that fulfil the full potential of proactive, holistic building simulations aiding decision making in the early design stages.

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