Early and detailed design stage modelling using Passivhaus design; what is the difference in predicted building performance?

EARLY AND DETAILED DESIGN STAGE MODELLING USING PASSIVHAUS DESIGN; WHAT IS THE DIFFERENCE IN PREDICTED BUILDING PERFORMANCE?

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ABSTRACT

In an effort to minimise the energy consumption in buildings, designers currently use a variety of energy simulation programs. However, despite the fact that those programs can make a significant contribution to the design of low energy buildings during the early design stage, the lack of detailed design information at that phase results in uncertainty in the modelled performance of the building. The uncertainty in building performance prediction has been the subject of previous research, yet no research to date has investigated the impact of design detail on the certainty of the performance prediction, this being the subject investigated in this paper.

The paper reviews the potential source of design uncertainty at the early design stage, and investigates the impact of such uncertainty on the modelled performance of a small community centre located in the UK, this building being constructed to the Passivhaus standard. Although it is common for early design stage performance modelling tools to be different to those used in detailed design, this study is based on the use of the EnergyPlus simulation platform for both the early and detailed design performance prediction; this removes any uncertainty due to changes in the modelling tool, and allows conclusions to be drawn directly about the impact of design detail on the performance prediction.

INTRODUCTION

Integrating building performance simulation into the early design stage

According to the Climate Change Act 2008 implemented by the UK Government for the minimisation of the increased climate change, in 2050 the net national carbon account must be at least 80% lower than the 1990 baseline (UK Government, 2008). In order to achieve this significant decrease and given the fact that buildings are greatly contributing to the high levels of greenhouse gas emissions, many building designers incorporate building performance simulation (BPS) into the design process. As also stated in the Green Overlay to the RIBA Outline Plan of Work (Gething, 2011), advanced modelling is a key element of the design process even from the conceptual stage, as it allows designers to verify the performance of a building model before finalising it.

However, it is still not very common for building designers and architects to integrate BPS into the conceptual stage of the design process, despite the fact that the decisions that are determined at that stage can contribute significantly and lifelong in the energy consumption of a building. In most cases, BPS tools are incorporated later in the design process serving as a tool for the evaluation of the energy performance of the building, which is crucial for ensuring the accreditation by a green building rating system. But even in the case that designers integrate BPS into the early design stage, the lack of detailed information related to the building’s form, construction and operation at that phase leads to many assumptions and consequently to great levels of uncertainty between the early and final design stages (Macdonald, 2002).

Identifying the sources of uncertainty

By implementing an uncertainty and sensitivity analysis within a real case study, Hopfe and Hensen (2011) have shown that taking into account the different categories of uncertainty can inform and boost decision making and therefore enhance design robustness. The classification of the various sources of uncertainty into two main categories, epistemic and aleatory, has been applied by many researchers (Dessai and Hulme, 2004, Helton et al., 2006, Der Kiureghian and Ditlevsen, 2009). The main criterion of that classification is reducibility, as “uncertainties are characterised as epistemic, if the modeller sees a possibility to reduce them by gathering more data or by refining the model, and as aleatory if he/she does not foresee the possibility of reducing them” (Der Kiureghian and Ditlevsen, 2009).

Despite the fact that the exhaustive list may differ from case to case, Kennedy and Hagan (2001) have also acknowledged that the sources of uncertainty could be classified into some prevalent categories. In this way, there is the parameter uncertainty which is a result of not knowing the real values of all the inputs; the parametric variability that is caused by the fact that some inputs may have not been specified and thus vary within a range of values; the model inadequacy which is due to the fact that there is no perfect model and consequently there is always an inconsistency between the predicted and real value; the observation error that is related to the variability of the experimental measurements and may also be a part of the residual variability of a model; and the code uncertainty which is related to the fact that, in practice, the relationship between a specific combination of inputs and its output is not known until the computer code is run.

Even though these categorisations may still be controvertible, however they could contribute to define and subsequently minimize the sources of uncertainty prior to decision making. Distinguishing epistemic from aleatory uncertainty could be applied into several study areas such as the energy performance prediction of buildings. As mentioned earlier, one of the main sources of the uncertainty between the early and final design performance prediction is the lack of detailed information concerning the various design variables of the building, which are related to its geometry, structure, materials, HVAC system and control strategy. However, while proceeding to the final design stage, the amount of detailed information is increased and the number of choices that are related to the form, construction and operation of the building are greatly reduced, eliminating this type of uncertainty - the epistemic uncertainty.

On the other hand, the increase in the design detail does not result in the elimination of the uncertainty that is connected to more probabilistic parameters such as the occupancy or the airtightness of the building which remain unknown even at the end of the design process - the aleatory uncertainty. It could be stated that this type of uncertainty can only be reduced after the completion of the building, when for example an air pressure test can be performed to specify its airtightness performance. Even though this *a posteriori* knowledge is crucial for obtaining the certification by an energy performance standard such as the Passivhaus Standard (McLeod et al., 2014), it is not beneficial for predicting the energy performance of the building and therefore cannot be used as an uncertainty quantification method for informing decision making during the design process.

Quantifying the uncertainty

In an effort to organise the design process and reduce its inherent uncertainty, RIBA has established the Plan of Work (Sinclair, 2013), a framework for building design and construction which subdivides building projects into eight stages identified by the numbers 0-7[1]. For stage 2, the main goal is the preparation of concept design including preliminary costs and sustainability plans that are related to the selection of materials, control strategies and systems. These can be achieved by addressing early on in the design process major design parameters such as the orientation, plan dimensions, building form, materials, glazing proportion and shading strategy, as they can influence significant performance criteria such as the energy, natural ventilation, daylight and airtightness of the building (Gething, 2011).

However, in real practice, this information may not be available during the early design phase or may change by the end of the design process, hindering the accurate generation of the building model and consequently the precise prediction of its energy performance. As stated in the CIBSE Guide L about Sustainability (Cheshire and Grant, 2007), a significant step in enhancing the energy efficiency of a building at the early design stage is to define its energy demand profile by adjusting the provided benchmarks to the distinct conditions and specifications of the building. In the UK, the energy efficiency requirements are included in four Approved Documents of the Building Regulations[2], which provide vital information for the design of new and existing buildings such as the limiting values for their fabric parameters. In the Passivhaus Standard, the range of those values is even narrower (table 1), a fact that reduces the range of the predicted energy performance and consequently the scope of the associated uncertainty.

Hence, building regulations can help to increase the available information during the early design stage and therefore reduce the number of design choices by eliminating infeasible solutions. However, since at that phase the inputs - the design details - are not specified accurately but vary within a range of values, there is still an uncertainty in the simulation output - the energy performance prediction - that needs to be quantified. As the common deterministic approach of predicting the future energy performance by fixing design details at present would not be able to deal with the uncertainty in parametric variability, a probabilistic approach should be adopted. In this way, the probability distribution for the values of the uncertain parameters should be identified, followed by generating several combinations of parameter values and running the model for each of these samples.

Random or Latin hypercube sampling methods have been commonly applied in uncertainty quantification in building performance analysis (De Wit and Augenbroe, 2002, Hopfe, 2009, Lee et al., 2013, Macdonald, 2009). Dessai and Hulme (2004) have also claimed that “where is possible, uncertainty needs to be quantified”, encouraging the use of probability based methods. However, “this depends on the type of the uncertainty being considered” or,

[1] 0) Strategic Definition, 1) Preparation and Brief, 2) Concept Design, 3) Developed Design, 4) Technical Design, 5) Construction, 6) Handover and Close out, and 7) In Use

[2] L1A (for new dwellings), L1B (for existing dwellings), L2A (for new buildings other than dwellings), and L2B (for existing buildings other than dwellings).

Table 1 The U-values for compliance with the Passivhaus Standard and Building Regulations 2010 as well as the values that have been used in both models.

Design component	**Limiting U-value, Passivhaus Standard** ($Wm^{-2}K^{-1}$)	**Limiting U-value, Building Regulations 2010** ($Wm^{-2}K^{-1}$)	**U-value for model parts complying with the Passivhaus Standard** ($Wm^{-2}K^{-1}$)	**U-value for model parts not complying with the Passivhaus Standard** ($Wm^{-2}K^{-1}$)
Wall	≤0.150	≤0.350	0.118	0.350
Roof	≤0.150	≤0.250	0.104	0.245
Floor	≤0.150	≤0.250	0.131	0.250
Glazing unit	≤0.800	≤2.200	0.780	2.160
Door	≤0.800	≤2.200	0.728	2.199

in other words, there are still many limitations in the quantification of the different types of uncertainty, mainly of aleatory uncertainties that cannot be specified easily. Another significant limitation is the difficulty in defining the mean value and standard deviation of the unknown parameters in order to perform their probability distribution. All these obstacles are even greater at the early design stage where there are a high number of unknown parameters, this complicating the implementation of an uncertainty quantification method.

RESEARCH AIM AND METHODOLOGY

The aim of this research is to investigate the uncertainty in predicting the performance of a building at different stages of the design life-cycle; in particular, this paper compares the uncertainty in predicting energy use at the concept and detailed design stages. The research will consider sources of both epistemic and aleatory uncertainty, and will investigate the extent to which epistemic uncertainty is reduced as design detail is finalised. It will also investigate the proposition that since optimization methods identify design solutions that meet one or more goals set by the designer, they provide a means of reducing the epistemic uncertainty associated with the choice of a particular design solution.

In this preliminary study, an exhaustive - "brute force" - search method is used to simultaneously identify the optimized design solutions and to generate samples for the uncertainty analysis. All parameters are treated as having a uniform probability distribution with only two values for each parameter being sampled – these representing the range limits of each parameter.

The number of parameters, parameter values, and their probability distributions will be extended in future research. The increased scale of problem will require the implementation of a probabilistic population based optimization method – in particular an evolutionary algorithm (Evins, 2013). The optimization approach will be extended to provide probabilistic design objectives, the probability being a result of the aleatory uncertainty (Van Gelder et al., 2014). Samples for use in a sensitivity analysis associated with the epistemic uncertainty in the design parameters will be extracted directly from the results of the optimization (Wang, 2014). The work described in this paper provides an insight into the potential findings of more detailed and future studies.

CASE STUDY

Creating the simulation models

The selected building is a community centre located in Findhorn, Scotland and designed to incorporate an existing business (shop and café) and a new reception space for the visitors. Two models have been created for the same building, each model having a different

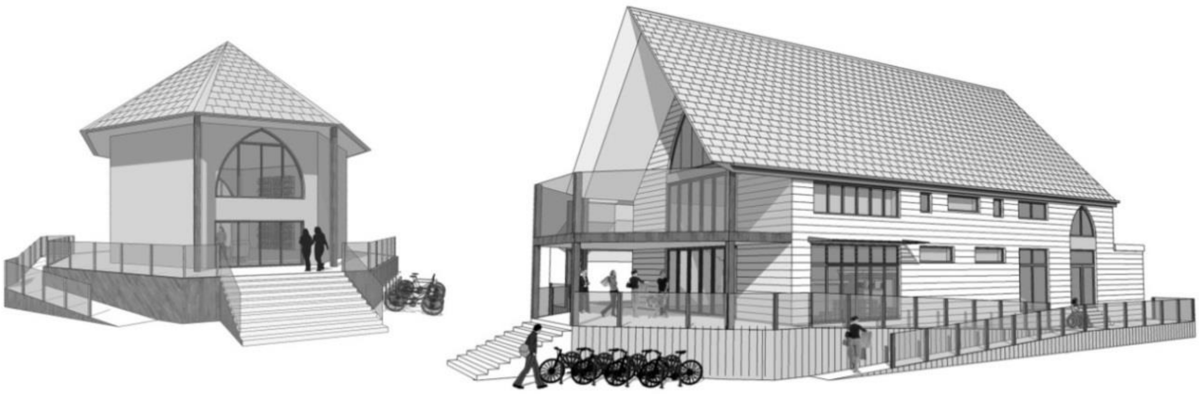

Figure 1 The early stage model (source: Eco Design Partnership).

Figure 2 The late stage model (source: Eco Design Partnership).

level of modelling detail: the first model responds to the initial design brief (early stage model, figure 1), while the other one responds to the final design brief (final stage model, figure 2). The geometry of the models has been built with respect to the material provided by the designers and consultants of the building (provided in the form of concept sketch designs for the early stage model and detailed drawings and specifications for the final stage model). According to the conceptual designs, a new building is going to house the existing business (shop and café), while a second building will accommodate the visitor centre and third party offices. However, according to the detailed drawings, the two separate buildings will finally be merged into one - incorporating the aforementioned uses - in an effort to reduce the number of surfaces and therefore minimise energy consumption and cost.

DesignBuilder has been selected for creating and simulating the two models, as it is a user-friendly modelling environment that enables the assessment of a range of environmental performance criteria of a building, such as its energy consumption, carbon emissions and comfort conditions by using a detailed simulation engine (EnergyPlus). After the creation of the geometry, the model data that are related to the construction, usage and operation of the building are defined and automatically exported to EnergyPlus for the simulation process. The simulation output is then automatically imported back to DesignBuilder and displayed in the form of text and/or graphics, facilitating the visualisation of the simulation results.

Complying with the regulations

To abide by the intention of the designers and their client, both models have been built to the Passivhaus Standard excluding some parts that do not comply with it, as they have not been integrated to the building envelope to further minimise cost (the visitor centre, third party offices and the storage rooms for both models and the shop offices for the late stage model). The Passivhaus Standard is an energy performance standard, developed in Germany in the early 1990s and aimed to reduce the heating and cooling loads of buildings without compromising their indoor air quality and comfort levels (Hopfe, and McLeod, 2015). As stated in the Passivhaus Primer (Mead and Brylewski, 2010), "a Passivhaus is a building, for which thermal comfort can be achieved soleley by post-heating or post-cooling of the fresh air mass, which is required to achieve sufficient indoor air quality conditions - without the need for additional recirculation of air".

Some of the most common characteristics of a Passivhaus building are the increased levels of insulation and airtightness, the minimisation of thermal bridges as well as the passive solar gains and internal heat sources. These principles are also translated into specific numerical targets and constraints, as for the compliance with the Passivhaus Standard both the Annual Specific Heating and Cooling Demand must be $\leq$ 15kWhm^{-2} (or the Specific Heating Load $\leq$ 10Wm^{-2} and the Annual Specific Primary Energy Demand $\leq$ 120kWhm^{-2}), while the Air Changes Per Hour must be $\leq$ 0.6 at 50Pa. In addition, the Mechanical Ventilation and Heat Recovery (MVHR) coefficient should be $\geq$ 0.75 (Mead and Brylewski, 2010). In table 1, limiting U-values are also provided for the design components of the building envelope with respect to the Passivhaus Standard specifications. For the parts of the building that do not comply with that standard, limiting U-values can even be higher, as defined by the UK Building Regulations 2010 and, more specifically, by the Approved Document L2A for non-domestic buildings (UK Government, 2013).

In the same table, the U-values that have been inserted in both models (early and final) of the building are also displayed. However, except for the Passivhaus parts of the final stage model where the U-values are based on the specifications provided by the material suppliers and thus they are known, the other numbers of the table represent the allowable values that could have been applied. For example, the

Table 2 The parameters that have been modified and their assigned values.

Parameter	Assigned value 1	Assigned value 2
U-value of external wall for non-Passivhaus parts (Wm^{-2}K^{-1})	0.157	0.350
U-value of roof for Passivhaus parts (Wm^{-2}K^{-1})	0.104	0.149
U-value of glazing unit for non-Passivhaus parts (Wm^{-2}K^{-1})	1.116	2.160
Infiltration rate for Passivhaus parts (ach^{-1} at 50Pa)	0.100	0.600
MVHR coefficient	0.750	0.900

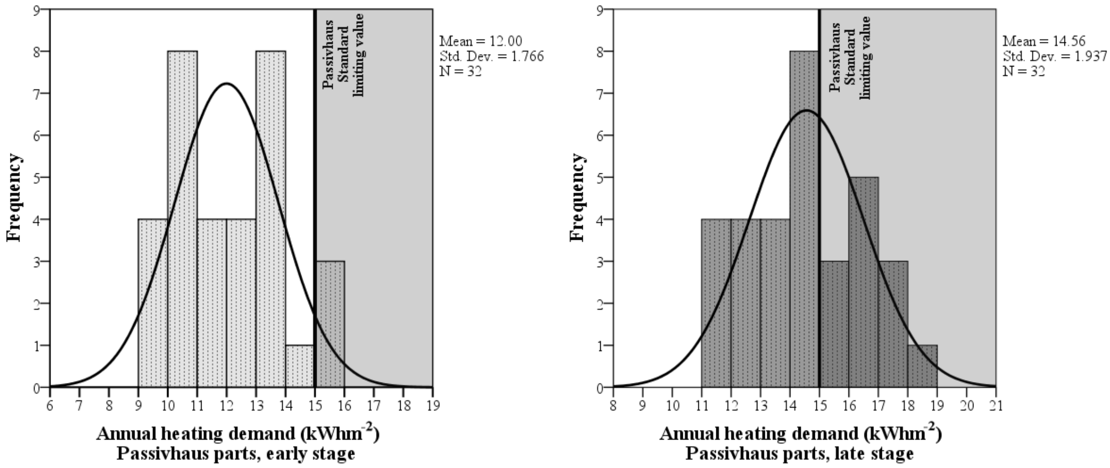

Figure 3 The frequency distribution of the annual heating demand for the Passivhaus parts of the building at the early (left) and late (right) design stage, as resulting from the 32 parameter combinations described in table 3. The grey area shows the results that become infeasible according to the Passivhaus Standard specifications.

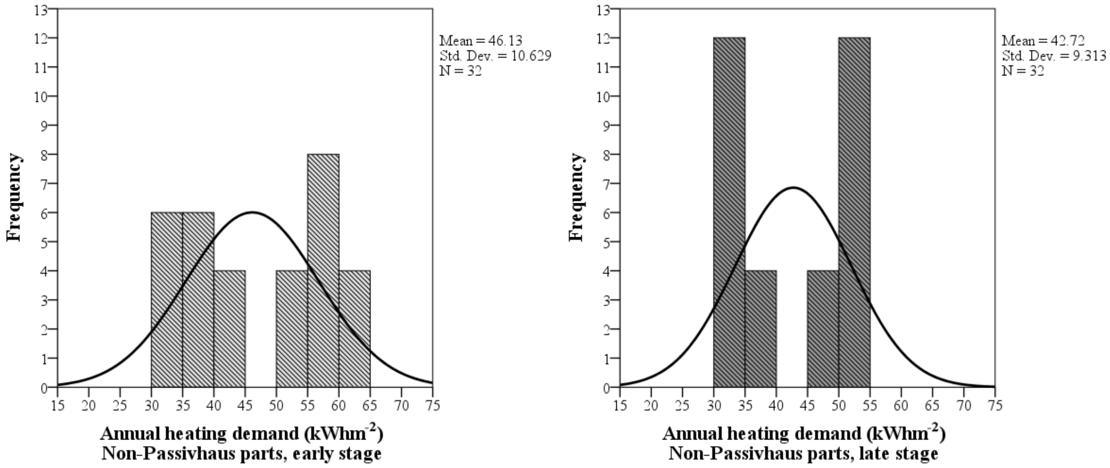

Figure 4 The frequency distribution of the annual heating demand for the non-Passivhaus parts of the building at the early (left) and late (right) design stage, as resulting from the 32 parameter combinations.

U-value for a wall (U_{wall}) to comply with the Building Regulations 2010 but not with the Passivhaus Standard could be any between 0.15 and 0.35 $Wm^{-2}K^{-1}$ ($0.15 < U_{wall} \leq 0.35$). In this case, as one of the goals of the study is to quantify the uncertainty in the prediction of the energy performance of the building, the applied U-values are close to the limits of the allowable values (table 2).

Quantifying the uncertainty

Although it is common for early design stage performance modelling tools to be different to those used in detailed design, this study is based on the use of the EnergyPlus simulation platform for both the early and detailed design performance prediction; this removes any uncertainty due to changes in the modelling tool, and allows conclusions to be drawn directly about the impact of design detail on the performance prediction. Hence, it could be stated that any uncertainty between the early and final design performance prediction is caused by modifications in the parameters of the model, these parameters either being related to the building's form, construction and operation or being more probabilistic such as its occupancy and infiltration rate.

In order to quantify these types of uncertainty for the selected building, an exhaustive sampling has been performed for both models. More specifically, as described earlier, the Passivhaus Standard and Building Regulations 2010 provide a range of allowable values for each of the design components. As it would be highly time consuming to assign and combine all these values for all the design components and as the aim of the preliminary work described in this paper is not to identify the optimum solutions within the feasible decision space but to investigate the uncertainty between the early and final performance prediction, only some of the design components of the building have been examined.

The model parameters that have been modified as well as their assigned values are shown in table 2. In order to examine the uncertainty that is related to more probabilistic parameters, the infiltration rate and MVHR coefficient have also been modified, with their assigned values being presented in the same table. To achieve an exhaustive combination of the selected parameters, 32 simulations have been conducted for each model: 2 external wall constructions for non-Passivhaus parts x 2 roof constructions for Passivhaus parts x 2 glazing units for non-Passivhaus parts x 2 infiltration rates for Passivhaus parts x 2 MVHR coefficients = 32 iterations (table 3).

LIMITATIONS

In order to investigate the difference in the predicted energy performance between the early and final design stage models, their annual heating demand in $kWhm^{-2}$ has been examined. Therefore, domestic hot water (DHW) volumetric consumption has not been included in the simulations, as it would not have any impact on the performed comparison. Concerning the internal gains from people, equipment, lighting etc., assumptions have been made wherever sufficient information has not been available, which have however been identical for both models. In addition, for both the early and final models, fresh air is provided exclusively by a MVHR unit.

The parameter combinations are based on the requirements of the Passivhaus Standard - and of the Building Regulations for the non-Passivhaus parts of the building. In an effort to investigate the impact of design details on the certainty of the performance prediction of the building, the applied values are relatively close to the limits of the allowable values. However, since the number of samples is limited, they can only give an impression of the difference in the predicted energy performance between the two models and not provide a holistic view of its range.

DISCUSSION AND RESULT ANALYSIS

The impact of the regulations

Compared to the Building Regulations, the Passivhaus Standard implies a more restricted range of allowable values that result in a narrower range of energy performance and consequently a narrower range of uncertainty. For the selected building, this can be testified by comparing figures 3 and 4, which display the frequency distribution of the annual heating demand in $kWhm^{-2}$ for the Passivhaus and non-Passivhaus parts of the building, respectively. Even though the number of the selected samples is limited, they provide an indication of the importance of the regulations on the range of the predicted energy performance. That impact can be determined by comparing the standard deviation of the annual heating demand between the parts of the building that are constructed to the Passivhaus Standard and those that do not comply with it; the standard deviation for the Passivhaus parts is 1.77 at the early design stage and 1.94 at the detailed design stage, while the corresponding numbers for the non-Passivhaus parts are 10.63 and 9.31, indicating a great difference in their distribution.

Another contribution of the regulations to the minimisation of the design uncertainty is the elimination of the solutions that do not fulfil their requirements. In this case, although figure 5 suggests that the total annual heating demand of the late stage model lies within the early stage demand, figure 3 indicates that for the Passivhaus parts, 3 parameter combinations at the early and 12 at the late design stage result in annual heating demand higher than $15kWhm^{-2}$. Therefore, according to the specifications of the Passivhaus Standard, these samples become infeasible, despite the fact that all the individual parameters fall within the allowable limits.

The difference in predicted energy performance

As illustrated in figure 5, the total annual heating demand of the late stage model lies within the early stage prediction, while it has a narrower distribution. However, since at the final stage the design is fixed - whether it is a good solution or not - the uncertainty that is related to its form and construction has been eliminated, and therefore any uncertainty at that phase stems from probabilistic parameters (the infiltration rate and MVHR coefficient in this case). Hence, in order to compare the difference in the predicted energy performance between the two stages, figure 6 displays the frequency distribution for all the 32 early stage samples, but for only 4 late stage samples of a fixed construction, this construction being the design alternative that leads to the minimum energy use (parameter combinations 21-24 in table 3). In this way, the mean annual heating demand is $22.81kWhm^{-2}$ at the early stage and $18.60kWhm^{-2}$ at the late stage, while the standard deviation is 3.81 and 1.88 respectively, which explains the narrower distribution of the final design and consequently its lower range of uncertainty.

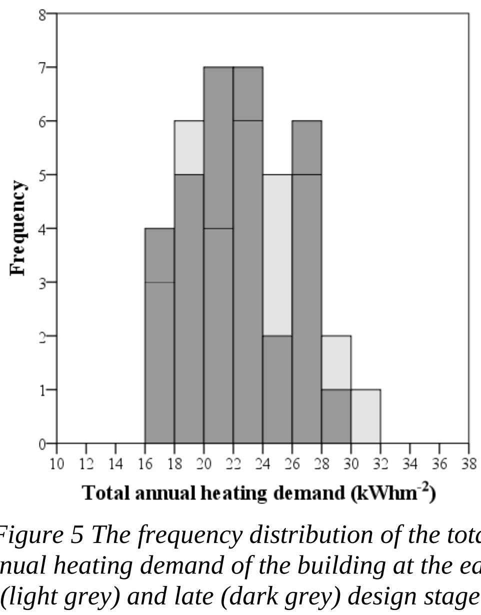

Figure 5 The frequency distribution of the total annual heating demand of the building at the early (light grey) and late (dark grey) design stage.

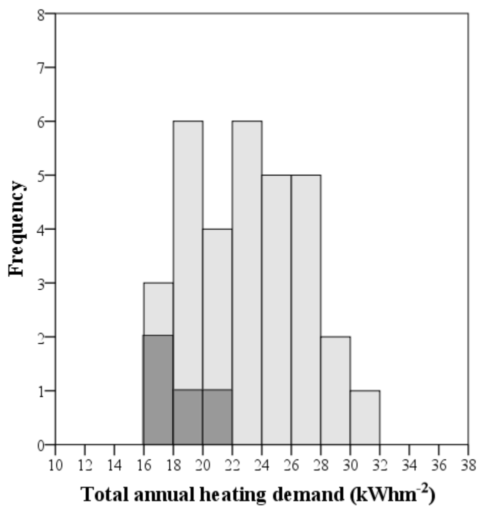

Figure 6 The frequency distribution of the total annual heating demand of the building at the early (light grey) and late (dark grey) design stage (for a fixed construction at late stage).

CONCLUSIONS AND FUTURE WORK

Two models have been created and simulated for a real case study building, in an effort to examine the difference in the predicted energy performance between the early and final design solutions and their inherent uncertainties. Even though quantifying the various uncertainties during the design process can support decision making, it can also entail several limitations, especially at the early design stage where there are a high number of unknowns. The contribution of the regulations has been proved to be vital for limiting the allowable values of the unknown parameters and eliminating infeasible solutions. Distinguishing epistemic from aleatory uncertainty can also help to predict the uncertainty of the final design, as while proceeding to the late stage, the amount of detailed information is increased and epistemic uncertainty is eliminated. Therefore, any uncertainty at that phase is aleatory, as it is dependent on more probabilistic parameters that cannot be known before the completion of the building.

However, within a real case study, the number and complexity of the design parameters are increased in an effort to conciliate various objectives that are often conflicting such as the aesthetics, functionality, energy efficiency and low cost of the building as well as the thermal comfort of its occupants. Hence, future research could focus on examining the role of multi-criterion optimisation in reducing epistemic uncertainty while helping designers to obtain a number of equally optimum solutions.

ACKNOWLEDGEMENTS

The contribution of the Eco Design Partnership is gratefully acknowledged for having provided all the project files and 3D models. This research is supported through a studentship funded by the UK Engineering and Physical Sciences Research Council (EPSRC).

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Table 3 The parameter combinations that have been inserted to DesignBuilder.

Parameter combinations					
	U-value of external wall for non-Passivhaus parts ($Wm^{-2}K^{-1}$)	**U-value of roof for Passivhaus parts** ($Wm^{-2}K^{-1}$)	**U-value of glazing unit for non-Passivhaus parts** ($Wm^{-2}K^{-1}$)	**Infiltration rate for Passivhaus parts** (ach^{-1} at 50Pa)	**MVHR coefficient**
1	0.350	0.104	2.160	0.100	0.900
2	0.350	0.104	2.160	0.100	0.750
3	0.350	0.104	2.160	0.600	0.900
4	0.350	0.104	2.160	0.600	0.750
5	0.350	0.104	1.116	0.100	0.900
6	0.350	0.104	1.116	0.100	0.750
7	0.350	0.104	1.116	0.600	0.900
8	0.350	0.104	1.116	0.600	0.750
9	0.350	0.149	2.160	0.100	0.900
10	0.350	0.149	2.160	0.100	0.750
11	0.350	0.149	2.160	0.600	0.900
12	0.350	0.149	2.160	0.600	0.750
13	0.350	0.149	1.116	0.100	0.900
14	0.350	0.149	1.116	0.100	0.750
15	0.350	0.149	1.116	0.600	0.900
16	0.350	0.149	1.116	0.600	0.750
17	0.157	0.104	2.160	0.100	0.900
18	0.157	0.104	2.160	0.100	0.750
19	0.157	0.104	2.160	0.600	0.900
20	0.157	0.104	2.160	0.600	0.750
21	0.157	0.104	1.116	0.100	0.900
22	0.157	0.104	1.116	0.100	0.750
23	0.157	0.104	1.116	0.600	0.900
24	0.157	0.104	1.116	0.600	0.750
25	0.157	0.149	2.160	0.100	0.900
26	0.157	0.149	2.160	0.100	0.750
27	0.157	0.149	2.160	0.600	0.900
28	0.157	0.149	2.160	0.600	0.750
29	0.157	0.149	1.116	0.100	0.900
30	0.157	0.149	1.116	0.100	0.750
31	0.157	0.149	1.116	0.600	0.900
32	0.157	0.149	1.116	0.600	0.750