Quick Energy Prediction and Comparison of Options at the Early Design Stage

Abstract: The energy-efficient building design requires building performance simulation (BPS) to compare multiple design options for their energy performance. However, at the early stage, BPS is often ignored, due to uncertainty, lack of details, and computational time. This article studies probabilistic and deterministic approaches to treat uncertainty; detailed and simplified zoning for creating zones; and dynamic simulation and machine learning for making energy predictions. A state-of-the-art approach, such as dynamic simulation, provide a reliable estimate of energy demand, but computationally expensive. To reduce computational time requires the use of an alternative approach, such as a machine learning (ML) model. However, an alternative approach will cause a prediction gap, and its effect on the comparing options needs to be investigated. A plugin for Building information modelling (BIM) modelling tool has been developed to perform BPS using various approaches. These approaches have been tested for an office building with five design options. A method using the probabilistic approach to treat uncertainty, detailed zoning to create zones, and EnergyPlus to predict energy is treated as the reference method. The deterministic or ML approach has a small prediction gap, and the comparison results are similar to the reference method. The simplified model approach has a large prediction gap and only makes only 40% comparison results are similar to the reference method. These findings are useful to develop a BIM integrated tool to compare options at the early design stage and ascertain which approach should be adopted in a time-constraint situation.

Keywords: Probabilistic; Zoning; Energy Simulation; Machine Learning; Prediction Gap; Building Information Modelling (BIM).

1. Introduction

The energy-efficient building design is an essential exercise for every building project. The building design is an iterative process in which a designer develops and assess several design options based on their performance. The designer's intuitive ability to assess and compare options is an essential part of the design process [1]. Nevertheless, quick evaluation and analysis of the options using a set of established tools provide relevant information for this assessment [2,3]. The concept of performance-based design, which got traction in the past few years, is based on the use of computational modelling and simulation to assess design options [4–6]. Since energy-efficient building design is the need of the hour, effective use of building performance simulation (BPS) results is necessary to assess the design options [3].

Furthermore, a designer should focus on the energy performance from the early design stage as the decisions made at the early stage affect the performance with a lesser cost of changes [7,8]. However, the energy performance prediction, at the early stage, has several impediments such as expensive modelling efforts, uncertain building characteristics, and high computational time [9–14]. Moreover, it requires a solution, which is embedded in a modelling tool to reduce remodelling efforts and enables the assessment of several options within a few minutes [15]. Thus, we are developing Building Information Modelling (BIM) integrated tool to make quick energy prediction and compare options at the early design stage. However, this development requires investigation into various early-stage energy prediction approaches.

1.1 Prediction gap and the requirements of the early design stage

Computational modelling and simulation tools are used to assess building energy performance during the design phase. There are several sophisticated energy simulation tools such as EnergyPlus [16], TrnSys [17], ESP-r [9], and Modelica [18]. Achieving a high level of accuracy requires a detailed building energy model (BEM), which is computationally expensive. Still, there exist some performance gap between the simulated energy demand and the actual energy consumption due to limitations of the simulation tool [19–23].

Moreover, the design process requires a simulation tool, which provides BPS results exactly when it is required [24,25], i.e. computationally fast enough to fulfil the requirement of the early design stage. The need to reduce computational time requires simplification of the model and quick energy prediction tool, which will cause an additional error, i.e. prediction gap [26]. A large prediction gap will make the BPS results unreliable. However, a small prediction gap with a significant reduction in the computational time will be useful for the early design stage. Addressing the performance gap is a vast domain of research in itself, and many research works are focussing on validation of simulation tools [27]. This article focusses on the prediction gap and its effect on comparing design options.

At the early design stage, BPS results are used for the comparison and classification of several design options rather than accurate energy prediction of one option [28]. It must be noted that achieving a very high level of accuracy is time-consuming and unrealistic, as several details are still developing and several parameters related to building operation are uncertain [9,29]. However, it is worth investigating the prediction gap using different approaches and their effect on the comparison of options.

1.2 Uncertainty, energy modelling and high computational time for BPS

The uncertainty in the parameters relevant to energy modelling causes uncertainty in the predictions. Uncertainty in BPS have been categorised as – numerical, modelling, scenario, and design by de Wit, 2001 and Rezaee et al., 2015. From early design stage perspective, uncertainty caused by scenario and design parameters is more relevant as other uncertainties are related to detailed BEM and precise energy estimation. The usual practice to predict the energy performance for an average value of these uncertain parameters and rely on the expertise of analyst to compare design options. However, the uncertainty requires probabilistic energy prediction approach [30]. The probabilistic approach uses random sampling of uncertain parameters and predicts the energy demand of a few hundreds of models for one design option [31,32]. A statistical analysis of probabilistic energy prediction is performed to make a comparison under uncertainty [32]. The domain of social and behavioural sciences has widely used statistical tool to ascertain whether the effects of two treatments are different from each other [33]. In analogy to BPS, it is used to determine which one of the two options, has a better energy performance under uncertainty.

Energy modelling at an early design stage is complicated as most of the details of the building are not developed. A designer is expected to develop only the building envelope at this stage. Thus, the information about thermal zones, which is critical to developing a BEM, is not present in the model in the design model. Several researchers have published guidelines to

develop an energy model for the early design stage to achieve realistic energy predictions [34,35]. These guidelines include the selection of zoning strategy, approximation of thermal properties of building envelope and assumptions related to building use [36]. However, the selection of a zoning strategy remains an essential aspect of energy modelling at an early stage [37]. There have been a variety of approaches to automatically generate thermal zones such as one zone per floor, perimeter depth zoning, cardinal direction zoning, core and perimeter zoning [38–41]. Among these approaches, ASHRAE’s core and perimeter zone divisions approach are expected to yield the most reliable results and used widely at the early stage [34,42,43]. However, this approach requires expensive modelling efforts and computational time. In contrast, one zone per floor requires relatively fewer modelling efforts and computational time; but, with a prediction gap [44].

Dynamic energy simulation, which promises an accurate estimation of building energy, requires a high computational time. If one simulation is required to assess a design option, it is not computationally intensive and takes around five minutes for each design option. However, the probabilistic approach requires a simulation of a few hundreds of models for each design option. This situation makes dynamic simulations computationally intensive and makes them unfit for the early stage [45]. The need to reduce computational time requires the use of a quick energy prediction tool. The simpler methods such as quasi-steady-state method are relatively quick; but, fail to capture the dynamic behaviour of BEM and has a large prediction gap [46,47]. These simpler methods require calibration for specific building case [48–50]; hence, it is not possible to use these approaches in this research. Other researchers have proposed the use of data-driven approaches to predict energy demand when a task requires predicting energy demand of several thousand of design combinations [51–53]. Dynamic energy simulations are replaced by quick pre-trained machine learning (ML) model to reduce computational time. However, an ML model, which makes thousands of predictions in a second, will have a prediction gap and other limitations.

1.3 BPS and design process

BPS provides relevant information which could drive critical decision-making at an early stage [14,15]. Architects and designers, who are involved from the early design stages, make decisions about building form, facades, and material. But most of these decisions intuitive with little or no support of energy simulation tools [28]. However, the energy-efficient design is not intuitive, and energy simulation must be an integral part of the design process. Researchers have previously developed methods to integrate architectural modelling and energy simulation tool [1,11,54–56]. Dynamic energy simulation tool such as EnergyPlus [11] or Modelica [54,57] have been integrated into an architectural modelling tool. This integration was focussed on minimising remodelling efforts by extracting information from the BIM model to develop BEM [58–60]. There are only a few examples of this integration at the early design stage [11,61]. However, these examples do not consider uncertainty and high computational time. It requires quick ML models to reduce the computational time attributed to probabilistic energy predictions [52,62]. The integration of the ML energy predictions into BIM is another challenge which requires the extraction of design data for a specific ML model [44].

Few researchers have proposed using sensitivity analysis methods to support decision-making for energy-efficient design [31,63,64]. However, these methods also require energy prediction of a few hundreds of models. Thus, a quick integrated tool, aligned with the design times, is required to avail the information to support energy-efficient building design.

1.4 Aims and objectives

This article focusses on developing methods for quick energy prediction and comparing design options at the early stage. We are developing a tool which extracts relevant information from the architectural modelling tool, makes energy predictions, and compare design options. We assume a scenario in which the designer is interested in assessing options based on energy performance. The designer is expected to develop the building envelope for each option. The energy predictions need to consider several uncertain parameters, defined by a probability distribution function. We are analysing different approaches to consider uncertainty, generate thermal zones, and make energy predictions. This analysis is required to ascertain whether replacing a state-of-the-art approach by an alternative approach will change the result of comparing design options. The objective of using an alternative approach is to reduce the energy prediction time with a small prediction gap.

We are developing a BIM integrated tool to make energy prediction using a variety of approaches. Primarily, we used one state-of-the-art approach and one alternative approach to treat uncertain parameters, creating thermal zones, and energy predictions. These approaches are listed in Table 1. The alternative deterministic approach to treat uncertainty requires an expert energy engineer to consider the effect of uncertainty on BPS. In contrast, the probabilistic approach estimates energy performance by simulating a few hundreds of parameter combinations and use statistical analysis for comparison. Core and perimeter zones approach, proposed in ASHRAE standards, is used to creates a detailed energy model [65]. An alternative one-zone-per-floor approach is used to create a simplified model, which requires fewer modelling efforts and computational time. To reduce computational to a few minutes, we are using an alternative approach of ML models. One-zone-per-floor or ML model approach will cause a prediction gap. We will be investigating this prediction gap and its effect on the comparison of design option.

Table 1. Various approaches to treat uncertainty, zoning, and prediction tool

	State-of-the-art approach	Alternation approach
Uncertainty treatment	Probabilistic	Deterministic
Zoning strategy	Core and perimeter zones (detailed)	One-zone-per-floor (simplified)
Energy prediction	EnergyPlus	ML prediction

The objective is to deliver fast BPS results for comparing design options during the first hours of design. The scope is limited to comparing options for their energy performance, not to make an exact energy prediction. Furthermore, the decision-making at the early design stage is complicated as the designer needs to assess design options on multiple competing criteria such as structural, energy, indoor comfort and others [3,66,67]. This article presents methods to compare design options for their energy performance only.

2. Research methodology

The research methodology is presented in four sub-sections. Section 2.1 describes the reference EnergyPlus (EP) simulation model, which is used to collect data for different design configurations. Section 2.2 details out different approaches to address uncertainty, zoning strategy and energy prediction. Section 2.3 proposes methods to study different energy prediction approaches and their effects on the comparison of design option. Section 2.4 describes the implementation aspects of integrating proposed energy prediction methods into a BIM modelling tool.

2.1 Reference EnergyPlus simulation model

The analysis, presented in this article, requires data for several combinations of design parameters for both, making probabilistic energy prediction and training and testing ML model. However, it will be unrealistic to collect real-world data for such a vast combination of parameters. Hence, we are relying on readily available dynamic energy simulation tool, i.e. EnergyPlus. We developed a reference model and validated its predictions for a real-world building. The details of this model are documented in Appendix 1, and the data is made available online on Mendeley datasets [68]. This reference model is developed considering the early design stage; thus, using the core and perimeters zones division for creating zones. It shows good accuracy with an error of only 0.8% for heating and cooling energy predictions. Relevant design parameters are adjusted to generate the data for probabilistic predictions and training and testing ML model. The researchers have developed an automated program, which quickly generates an EP simulation model and runs parallel simulations to save time.

2.2 Details of different approaches used for energy prediction

The uncertainty in the parameters and missing zone information make energy simulation at early design stage a challenging task. Besides these issues, the high computational time required by dynamic energy simulations needs to be reduced. We selected one state-of-the-art approach and one alternative approach to address these issues. These issues and approaches are described in Figure 1. The designer needs to select an approach to treat uncertainty and zoning strategy. This information is used to develop BEM. Then, the designers select an energy prediction tool to make energy predictions and finally, the comparison of design options. Sub-sections 2.2.1, 2.2.2, and 2.2.3 provide the details of the approaches.

Figure 1. Primary and alternative approaches to energy prediction

2.2.1 Treatment of uncertainty in the parameters

This study considers two types of uncertain parameters - first, undecided design parameters such as u-values, which will be decided at the later design stage. Second, scenario parameters such as occupancy which will remain uncertain post-design phase or cannot be measured adequately. Uncertainty in the undecided design parameters captures the effect of lack of knowledge in those design aspects which are yet to be decided, such as thermal properties of the building envelope. The scenario parameters are boundary condition such as occupancy and light heat gain [31,69]. However, developing BEM requires this information. Such parameters are listed in Table 2.

Table 2. Details of uncertain parameters

Parameter category	Design parameters
Undecided design parameter	u-values of walls, ground floor, roof and windows, g-value of windows, airtightness, internal mass
Scenario parameters	Light and equipment heat gain, operating hours, occupant load, heat pump coefficients of performance (COP), boiler efficiency

The two approaches to treat uncertainty in the parameters are presented in Figure 2. One approach to treat this uncertainty is “deterministic”. The energy demand is predicted for the mean value of uncertain parameters. The results using a deterministic approach are described by one value for each option. However, this one value will not consider the effect of uncertainty in the parameters. Thus, comparing the options based on deterministic predictions requires an expert to account for uncertainty. For simplicity, we assumed a variation of $\pm 1.5\%$ energy predictions due to uncertain parameters. The energy prediction is visualised by the predicted value and variation, as shown in Figure 2. In this approach, a threshold for the difference is required to conclude that the two options have different energy performance. If a variation of $\pm 1.5\%$ is assumed; then, a difference of 3% is used to conclude that the two options have different energy performance. The value of this threshold is extremely crucial to make a comparison under a deterministic approach. We will be discussing the effect of choosing a different value, later in the article. The comparison under deterministic approach is performed as follows:

If $d_{O1, O2} < 3\% \text{ (threshold)} \Rightarrow \text{Comparison results} = \text{No Difference (ND)}$
Else if $E_{O1} < E_{O2} \Rightarrow \text{Comparison result} = \text{O1 is better (O1)}$
if $E_{O2} < E_{O1} \Rightarrow \text{Comparison result} = \text{O2 is better (O2)}$

Where E_{O1} and E_{O2} are energy prediction for design option O1 and O2 and $d_{O1, O2}$ is the percentage difference between them.

Another approach, to treat uncertainty, is “probabilistic”. In this approach, several random combinations of undecided design parameters are sampled based on their probability distribution. The energy demand is predicted for each combination, which is visualised by a mean value, 95% confidence interval and its probability distribution using the violin plot, as shown in Figure 2. The comparison is performed by running statistical analysis and calculating the probability value (p-value) for each comparison. A 95% confidence interval and the p-value is calculated using statistical analysis described in the following text. If the p-value is less than 0.05 (95% confidence level), i.e. statistically significant, then the building with lesser energy demand (mean value) is better. The comparison under probabilistic approach is performed as follows:

If $p_{O1, O2} > 0.05 \Rightarrow \text{Comparison results} = \text{No Difference (ND)}$
Else if $E_{O1} < E_{O2} \Rightarrow \text{Comparison result} = \text{O1 is better (O1)}$
if $E_{O2} < E_{O1} \Rightarrow \text{Comparison result} = \text{O2 is better (O2)}$

Where E_{O1} and E_{O2} are energy prediction for design option O1 and O2 and $p_{O1, O2}$ is the probability that the energy demand of the design options O1 and O2 are not different.

Figure 2. Different approaches to treat uncertainty in the parameters

Statistical analysis - A statistical analysis is performed to compare options using the probabilistic approach, in which the energy demand is predicted for several combinations of uncertain parameters. Figure 2 shows a probabilistic energy prediction for two design options, O1 and O2. The probability value (p-value) for each comparison is calculated using the Wilcoxon rank-sum test [70]. This test is a non-parametric alternative to student t-test and performs a pair-wise comparison of the options. Since the energy prediction data is not normally distributed, a non-parametric test is used. The test investigates whether the two samples selected from populations have the same distribution. A p-value of less than 0.05 means that there is a 95% probability that the two samples have different distributions. An analogy of this statement for comparing the design options will be p-value of less than 0.05 signifies that there is a 95% probability that the options have different energy performance. The number of samples affects the statistical tests. The number of samples required for this test depends on the type-I error, statistical power, standard deviation, and the true difference. The required number of samples (n), to achieve 90% of the statistical power with 5% of type-I error and, is given by the Eq. (1) [71].

$$n = 21 \frac{\sigma^2}{d^2} \quad \text{Eq. (1)}$$

Where σ is the standard deviation, and d is the true difference. The standard deviation is 8 square units (as found in 100 trial samples), and we assumed 2 MWh/a is the required true difference. Thus, the required number of samples is 336. The statistical analysis will be performed on 400 samples or 200 samples for each option.

2.2.2 Zoning strategy

The mass model represents a building at an early stage. Thermal zones and building elements, which are not present in this model, needs to be generated. The state-of-the-art and alternative zoning strategies are shown in Figure 3. We selected ASHRAE's core and perimeter zones to create a detailed zoning model [72]. In this approach, perimeter zones are created by offsetting each edge by a distance and a core zone in the centre. This approach represents the state-of-the-art approach as it provides the most realistic estimate of energy at early design stage [34,38,42,72].

In contrast, we selected one-zone-per-floor approach to create a simplified zoning model [41,44]. In this approach, one zone is created at each floor level. External walls, ground floors, internal floors, internal walls and roofs are generated using generic rules [44]. A window is generated in each external wall based on the window-to-wall ratio. Since there are no internal walls in a simplified model; we considered additional heat capacity of internal walls as thermal mass. Based on the approximation from the actual building, we considered additional heat capacity of 90 kJ/Km² for internal walls. This approach requires fewer modelling effort and computational time. Usually, an energy simulation for a simplified model takes one-third of the time compared to a detailed model.

Figure 3. Detailed and simplified model from a mass model

2.2.3 Selection of energy prediction tool

Dynamic energy simulations are used as a state-of-the-art approach to predict energy demand during the design stage. We are using EnergyPlus as a dynamic energy simulation tool in this research [16]. As these simulations require very high computational time, especially in the case of a probabilistic approach, an alternative approach of the ML model is used to provide quick energy prediction results. In this study, the ML model, proposed by Geyer and Singaravel, 2018 [52,62] and developed further by Singh et al. 2019, is used [73]. The details of the data used for training and testing model is presented in Appendix 2 and made available on Mendeley datasets [74]. The ML model is trained using the Keras and TensorFlow library in python [75]. The model shows an accuracy of 0.94 (R²) and root mean square error of 4.2 MWh/a. The accuracy of the model is tested on the random recti-linear building shapes with various combination of design parameters. Thus, ensuring the applicability of the model on the possible design variations at the early design stage. This ML model predicts energy demand of 1000 building configuration within two minutes.

2.3 Comparison of approaches

We are studying the effect of alternative approaches on energy prediction and comparing design options at the early stage. The energy prediction and comparison results obtained using state-of-the-art approaches are treated as a reference. Thus, in this article, the method comprising of a probabilistic approach to treat uncertainty, detailed approach to creating thermal zones, and dynamic simulation to make energy predictions will be treated a reference method (M1). An alternative method (M2) is used to study the effect deterministic approach to

treat uncertainty. An alternative method (M3) is used to study the effect of using the simplified model on the prediction gap and comparison results. An alternative method (M4) will be used to study the effect of using ML models instead of dynamic simulations. Table 3 lists all the proposed methods and the approaches used to make energy predictions.

Table 3. Description of four different methods used to make energy prediction

	Uncertainty treatment	Zoning strategy	Simulation Tool
Method 1 (M1)	Probabilistic	Detailed	EnergyPlus
Method 2 (M2)	Deterministic	Detailed	EnergyPlus
Method 3 (M3)	Probabilistic	Simplified	EnergyPlus
Method 4 (M4)	Probabilistic	Detailed	ML Prediction

Different approaches to energy predictions are compared based on three characteristics, modelling time, computational time, and accuracy. The researchers have developed an automated tool to create BEM from the BIM model. Thus, the modelling time is very less. However, creating a detailed model requires a little more time than the simplified model. Computational time represents the time required for making energy predictions, which is the most time-consuming step. Finally, the number of similar comparison results as the reference method defines the accuracy of a method. The alternative method is said to have good accuracy if it has the same comparison results as the reference method.

2.4 Implementation of the proposed methods

The proposed methods are implemented by developing a plugin for Revit, a proprietary BIM modelling tool from Autodesk [76]. This plugin is developed to make BPS results available to the designer without any remodelling efforts. This tool is capable of making deterministic and probabilistic energy predictions to treat uncertain parameters. The designer is allowed to use an appropriate zoning strategy to generate thermal zones. Moreover, to reduce computational time, it uses the pre-trained ML model. Different options designed by the designer are saved using a built-in function of Revit. After running this plugin, the relevant information is extracted from the BIM model, and uncertain parameters are provided with uncertainty using a user form. This plugin uses two programming languages C# (for interacting with Revit) and python (for ML predictions and statistical analysis). After making probabilistic predictions, the pair-wise comparison of design options is performed using statistical analysis. The energy prediction and comparison results are integrated into BIM tool by creating parameters and assigning a value to them. The screenshots of the plugin are shown in Figure 4.

Figure 4. Screenshot from the developed Revit plugin

3. Testcase

A typical medium-size office building with a total floor area of 1200 sqm with three-storey has been selected to demonstrate the proposed energy prediction methods. The building is located near Munich; thus, we are using weather data of Munich. The constructed building 'Tausendpfund' is shown in Figure 5 in the top-left corner. The building follows a typical 5-day schedule. More details of the simulation model are described in Appendix 1. The details of the design options, uncertainty in undecided design and scenario parameters are discussed in subsections 3.1, 3.2, and 3.3.

3.1 Design options at the early design stage

To mimic the early design stage, we have developed five design options for this building. Option 1 is a box-shaped building which is the same as the constructed building. Option 2, 3 and 4 are three options with 'L', 'T' and 'S' floor plans, respectively, as shown in Figure 5. These represent the typical floor plan shapes for office buildings [77,78]. Option 5 is introduced to represent the most compact option among these, which has a square floor plan.

It should be noted that each option has three-storey and the same floor area. Besides the floor plan, the designer has developed the rough geometry of facades, from which the window-to-wall ratio is the relevant information. In the constructed building, WWR is 0.33 in all the directions, which results in the total window to floor area ratio of 22.5%. Thus, we have used

the same window to floor area ratio for all the options. However, slight modifications are made to mimic variation among different facades. For examples, options 2, 3, and 4 have WWR (North) 0.5, WWR (South and East) 0.35 and west walls have no windows.

Figure 5. Description of design options

3.2 Uncertainty in undecided design parameters

These are design parameters which will be decided later stage of design. Since the designer can select any value from the possible values, the uncertainty in these parameters is represented by a uniform distribution function [31,79,80]. A parameter has an equal probability of taking any value in the given range. Further, we are keeping the mean value of these parameters as in the real building. The possible variations are assumed based on the thermal resistance requirements. We investigated two possible variations in these parameters to represent high and low uncertainty. The two levels of uncertainty represent the effect of different uncertainties on BPS. These parameters are listed in

Table 4.

Table 4. Mean values and ranges of undecided design parameters

	Parameter	Unit	Mean Value	Variation	
				High	Low
Undecided design parameters (Uniform Distribution)	u-value (wall)		0.18	0.02	0.01
	u-value (ground floor)	W/m ² K	0.19	0.02	0.01
	u-value (roof)		0.15	0.02	0.01
	u-value (windows)		0.87	0.07	0.035
	g-value (windows)	-	0.35	0.14	0.07
	Airtightness	ACH	0.3	0.1	0.05
	Internal mass	kJ/Km ²	30	15	7.5

U-value of walls, ground floor, and roof – The real building has a u-value of 0.18 (walls), 0.19 (ground floor), and 0.15 (roof). These u-values are achieved by installing an insulation

layer with thermal conductivity of 0.035 and thickness of 180 mm (walls), 60 mm (ground floor), and 230 mm (roof). Passive house standard requires a u-value of 0.15 W/m²K for all opaque components [81]. EnEV standards specifies the maximum u-values of 0.28 (walls), 0.28 (ground floor), and 0.2 (roof) [82]. However, these values represent an extreme which will not be suitable for an energy-efficient building. Hence, to represent possible variation, we have taken a mean value as in the real building and a variation of ± 0.02 for high uncertainty and ± 0.01 for low uncertainty. The assumed variation in u-values is possible to achieve by installing insulation layer in varying thickness; not exceeding 250 mm.

Windows – The windows have triple glazing pane with u-value of 0.6 and frame with u-value of 1.25. This arrangement results in an overall u-value of 0.87 W/m²K. The overall g-value of the window with moderate solar gain glazing will be 0.35 (0.5 for the glazed part). We considered double glazing windows and highly insulated triple glazing windows to represent possible variations. Double glazed windows have overall u-value of 0.94 and g-value of 0.5 (0.71 for high solar gain glazing) and highly-insulated triple glazing windows have overall u-value of 0.8 and g-value of 0.21 (0.3 for low solar gain glazing). Thus, we assumed the u-values of windows is 0.87 and g-value 0.35 as mean. We assumed the possible variation of ± 0.07 (u-value) and ± 0.14 (g-value) under high uncertainty and ± 0.035 (u-value) and ± 0.07 (g-value) under low uncertainty.

Airtightness – DIN 18599-2 specifies an air permeability of 3 (category I), 6 (category II), 9 (category III) and 15 (category IV) for buildings. This air permeability results in approximate infiltration (depending on the surface to volume ratio) caused due to leakages and windows of 0.2 ACH (category I), 0.3 ACH (category II), 0.4 ACH (category III), 0.6 ACH (category IV). We considered category I, II and III construction in this article, as category IV construction represents the presence of apparent cracks and sub-standard from an energy-efficiency perspective. The real building is a category II building with an infiltration rate of 0.3 ACH. We assumed a possible variation of 0.1 under high uncertainty and 0.05 under low uncertainty.

Internal mass – The internal mass is considered to capture the effect of the thermal mass of and furniture. Johra et al., 2017 has approximated thermal inertia of 30 kJ/Km² because of furniture in a medium-furnished office building [83]. We assumed ± 15 (50%) under high uncertainty, and ± 7.5 (25%) in this value as a correct estimate will not be possible.

3.3 Uncertainty in scenario parameters

The scenario parameters are the boundary conditions and considered as targeted values by the design team. These parameters are expected to follow a normal distribution as the design team targets for a mean value. We have taken the mean value of these parameters as the real building and standard deviation of 10% of the mean value based on previous studies [80,84]. These parameters are mentioned in Table 5. The building has an average light heat gain of 6 W/m² to provide a lighting level of 500 lux as required for office use. The building has an equipment heat gain of 12 W/m², as estimated based on the number of work and other equipment expected to be in the office space. The building has a usual occupancy of 50 persons, which translates to approximately 24 m² per person. The building is expected to operate for 11 hours a day, starting at 8 AM till 7 PM. The building is fitted with a heat pump to provide heating and

cooling both. The rated coefficients of performance (COP) are 2.8 for heating operation and 3.6 for cooling operation. The building has a boiler with a rated efficiency of 0.95. We limit the value of boiler efficiency to 0.98, as a higher value will be unrealistic.

Table 5. Mean values and standard deviation for scenario parameters

	Parameter	Unit	Mean value	Standard deviation
Scenario parameters (Normal Distribution)	Light heat gain	W/m ²	6	0.6
	Equipment heat gain		12.5	1.25
	Occupant load	m ² / Person	24	2.4
	Operating hours	Hours	11	1
	COP (Heating)		2.8	0.28
	COP (Cooling)	-	3.6	0.36
	Boiler efficiency		0.95	0.03

4. Results

The BPS results using different approaches are presented in four sub-sections. Sub-section 4.1 focusses on the energy prediction results using different methods and the prediction gap. Sub-section 4.2 presents a comparison of design options using different energy prediction methods. Sub-section 4.3 compares alternative methods against the reference method to observe the changes in the comparison results. Sub-section 4.4 provides an overall comparison of different energy prediction approaches.

4.1 Energy prediction using different methods

We are predicting the energy demand of five design options using four different methods under high and low uncertainty. The energy prediction results are presented to observe the prediction gap and compare the energy performance of the options. Figure 6 visualises the energy prediction for two design options using different methods. The mean values of energy predictions, for ‘Box’ option, are 66.4 (M1), 65.1 (M2), 69.4 (M3), 66.3 (M4) MWh/a. Assuming M1 as a reference method, methods M2, M3, and M4 have a prediction gap of 1.3 (2%), 3 (5%) and 0.2 MWh/a, respectively. Similarly, for, ‘L’ option, these prediction gaps are 1.1 (2%), 0.9 (1%), and 0.7 (1%) for methods M2, M3, and M4, respectively. It is worth noticing here that the prediction gap is the highest for method M3, which uses a simplified model approach.

After observing the prediction gap for two specific options, we are visualising the energy prediction results for all the options under two uncertainty conditions in Figure 7. It is noticeable that the energy prediction is more certain under low uncertainty conditions. For example, the 95% confidence interval for the ‘Box’ option is 1.01 MWh/a for high uncertainty which reduces to 0.63 MWh/a for low uncertainty. The similar trend follows for other options using any probabilistic energy prediction method.

Method M1 and M2 defer on the approach to treat uncertainty. The mean value of prediction, using method M2, is always lower than the method M1. The maximum prediction gap is 1.1 MWh/a for high uncertainty and 0.6 MWh/a for low uncertainty. Methods M1 and M3 defer

on the approach of creating zoning divisions. The maximum prediction gap is 2.9 MWh/a using method M3. However, for some options, this gap is more noticeable such as ‘Box’ and ‘Square’. Mostly, the simplified approach makes an energy prediction more than the detailed approach; but for some option, it is lower. Method M1 and M4 defer on the approach of making energy prediction using EnergyPlus or ML model. The energy prediction from these two methods are quite comparable, and the prediction gap is small. The maximum prediction gap is 0.9 MWh/a for high uncertainty and 0.5 MWh/a for low uncertainty.

Figure 6. Prediction gap using different methods

The average value of 95% confidence interval for all the option using method M1 is ± 1.03 MWh/a under high uncertainty and ± 0.64 MWh/a under low uncertainty. In most of the cases, the difference between the mean energy prediction of two options (such as options ‘Box’ and ‘T’), is more than this value. This observation suggests, it is possible to differentiate between two options under uncertainty. However, the extreme values, i.e. the highest and lowest energy prediction, varies ± 8 MWh/a from the mean value.

Figure 7. Energy prediction using different methods under high and low uncertainty

4.2 Comparison of design options using different methods

This section presents the results of comparing design options using different methods of energy prediction. In total, there are five design options which require ten pair-wise comparisons. Moreover, we have two uncertainty conditions, so the total number of comparisons is 20 for each method, as presented in Table 6. The comparison is based on the criteria described in the methodology section. The comparison in which it is concluded that one option is better than other, the cell is highlighted by shading and bold letters. The comparison results, under high uncertainty, are presented in the upper right corner, and under low uncertainty in the lower-left corner. The p-value of the comparison (for probabilistic approach) and percentage difference (for deterministic approach) is calculated for each comparison. The result of the comparison, whether there is no difference (ND) or an option is better than other, is written in the brackets.

Table 6. Comparison of design options using different methods

Comparison of design options using method M1					
Options	Box	L	T	S	Square
Box		0.01 (Box)	0.0 (Box)	0.01 (Box)	0.24 (ND)
L	0.0 (Box)		0.55 (ND)	0.74 (ND)	0.0 (Square)
T	0.0 (Box)	0.39 (ND)		0.72 (ND)	0.0 (Square)
S	0.0 (Box)	0.63 (ND)	0.62 (ND)		0.0 (Square)
Square	0.07 (ND)	0.0 (Square)	0.0 (Square)	0.0 (Square)	
Comparison of design options using method M2					
Options	Box	L	T	S	Square
Box		3.19 (Box)	3.8 (Box)	3.49 (Box)	1.34 (ND)
L	3.19 (Box)		0.61 (ND)	0.3 (ND)	4.53 (Square)
T	3.8 (Box)	0.61 (ND)		0.3 (ND)	5.14 (Square)
S	3.49 (Box)	0.3 (ND)	0.3 (ND)		4.84 (Square)
Square	1.34 (ND)	4.53 (Square)	5.14 (Square)	4.84 (Square)	
Comparison of design options using method M3					
Options	Box	L	T	S	Square
Box		0.84 (ND)	0.3 (ND)	0.84 (ND)	0.25 (ND)
L	0.7 (ND)		0.39 (ND)	0.66 (ND)	0.33 (ND)
T	0.08 (ND)	0.17 (ND)		0.22 (ND)	0.92 (ND)
S	0.75 (ND)	0.5 (ND)	0.05 (T)		0.19 (ND)
Square	0.06 (ND)	0.13 (ND)	0.84 (ND)	0.04 (Square)	
Comparison of design options using method M4					
Options	Box	L	T	S	Square
Box		0.0 (Box)	0.0 (Box)	0.0 (Box)	0.71 (ND)
L	0.0 (Box)		0.37 (ND)	0.6 (ND)	0.0 (Square)
T	0.0 (Box)	0.26 (ND)		0.64 (ND)	0.0 (Square)
S	0.0 (Box)	0.57 (ND)	0.52 (ND)		0.0 (Square)
Square	0.78 (ND)	0.0 (Square)	0.0 (Square)	0.0 (Square)	

The comparison of options using method M1 does not change for low and high uncertainty, except the p-value are smaller for low uncertainty. In 12 out of 20 comparisons, the method concludes one option is better than others based on its energy performance. The method suggests that options ‘Box’ and ‘Square’ have the same energy performance. Similarly, options ‘L’, ‘T’, and ‘S’ have a similar energy performance based on a statistical analysis of probabilistic predictions.

For method M2, the comparison results are the same as method M1. However, we need to observe the percentage difference in mean energy prediction between two options. The highest difference is 5.14% which is for comparing options ‘Square’ and ‘T’, and the lowest is 0.3. We assumed a threshold of 3% and the method shows the same comparison results as method M1, with 12 out of 20 comparisons suggesting one option is better. However, if another threshold

is selected, such as 4%, then this number will be reduced to 6 out of 20. Similarly, for a threshold of 5%, there will be only two such comparisons.

Most of the comparisons using method M3 leads to no difference. In only two cases, it suggests one option is better than others. The large and varying prediction gaps for different options lead to different comparison results from method M1.

The comparison results are mostly the same for method M4 and M1. There is a slight difference in the p-values using method M4 and M1; but, it does change the comparison results. A small prediction gap while replacing dynamic simulations by ML model supports this observation.

4.3 Change in the comparison results using alternative approaches

This section presents the changes in the comparison results when an alternative approach is used instead of a state-of-the-art approach. Method M1 is treated as a reference as it uses a state-of-the-art approach to treat uncertainty, zoning, and make predictions. The changes in the comparison results, when using methods M2, M3, and M4, are presented in Table 7. If an alternative method has the same comparison results as method M1, it is marked with '✓' else '×'.

First, we are observing the comparison results using method M1 and M2. There is no change in the comparison results when a deterministic approach. However, it should be noted that the comparison under deterministic approach depends on the threshold set by an expert (3% in this case). Hence, it will change and will lead to a wrong comparison if the threshold is set incorrectly. While comparing results from method M1 and M3, there are many different comparison results. The simplified model approach only has eight comparison results similar to the reference method. The use of the ML model (M4) instead, EnergyPlus (M1) does not change any comparison results.

Table 7. Change in the comparison results using alternative approaches

Probabilistic vs deterministic approach (M1→M2)					
Options	Box	L	T	S	Square
Box		✓	✓	✓	✓
L	✓		✓	✓	✓
T	✓	✓		✓	✓
S	✓	✓	✓		✓
Sq.	✓	✓	✓	✓	
Detailed vs simplified model approach (M1→M3)					
Options	Box	L	T	S	Square
Box		×	×	×	✓
L	×		✓	✓	×
T	×	✓		×	×
S	×	✓	✓		✓
Sq.	✓	×	×	×	
EnergyPlus vs ML model approach (M1→M3)					
Options	Box	L	T	S	Square
Box		✓	✓	✓	✓
L	✓		✓	✓	✓
T	✓	✓		✓	✓
S	✓	✓	✓		✓
Sq.	✓	✓	✓	✓	

4.4 Comparison of energy prediction methods

In this section, different methods M1, M2, M3, and M4 are compared based on modelling time, prediction time, and accuracy of comparing design options. It must be noted that the modelling time is the time required by the tool to automatically generate zones and write the required information to make energy prediction. The prediction time is the time required by EnergyPlus or ML model to make energy predictions. Accuracy of comparing design options is the number of the same comparison results as the reference method M1. The different methods are compared in Figure 8, based on the mentioned parameters. The tests are performed on a computer with a Core i5 CPU with a clock speed of 1.9 GHz and running six simulations in parallel. The method M1 will be requiring the highest time for both modelling and prediction.

In comparison, method M2, M3, and M4 will require slightly less time. The prediction time is less for method M2, as it only requires one simulation for each design option. Method M4 also requires only 8 minutes to make energy prediction using the ML model. Both methods M2 and M4 have the same comparison results as method M1. However, method M3 only make 40% of the same comparison results as method M1.

Figure 8. Comparison of different energy prediction methods

5. Discussion

The article presents different approaches to make energy prediction and compare design options at the early design stage. Primarily, it focusses on the issues of uncertainty, zoning, and high computational time. The researchers have selected one state-of-the-art and one alternative approach to address the mentioned issues. While the state-of-the-art approach provides the most reliable BPS results, the time required for energy modelling and prediction is significantly high. The alternative approaches are time-efficient, as required to align BPS with the design process, but have a prediction gap. Hence, for using BPS effectively at the early stage, the efficacy of an alternative approach is assessed using a test case building. A plugin for BIM modelling tool has been developed to implement different energy prediction methods. The method using a probabilistic, detailed model and EnergyPlus simulation approach, which gives the most reliable results, is treated a reference method. An EnergyPlus model using a detailed model approach is developed and validated it for real building data to obtain reliable BPS results using the reference method.

The energy predictions using an alternative approach are slightly different from the reference method, i.e. there exist prediction gap. However, this prediction gap may or may not change the results of comparing design options. The method M2, which uses a deterministic approach to treat uncertainty has a small prediction gap (max. 1.1 MWh/a). Moreover, the mean value using method M2 is always lower than method M1 and do not affect the result of comparing design options. However, this approach is debatable as it makes a deterministic prediction for an uncertain scenario and relies on an expert's judgment to decide a threshold for comparing options. The different values of the threshold will lead to different comparison results. We have selected a small value of threshold (3%) to conclude that the energy performances of two design options are different. The threshold of 4% and 5% will suggest that the two options have the same energy performance, which will be incorrect in the situation under consideration.

The prediction gap caused by the simplified model approach instead detailed model approach is of particular interest here. For some options such as 'Box' and 'Square', this gap is relatively more prominent than other options. Moreover, the gap widens to 2.9 MWh/a and for some

options, and it is negative and for some options and positive for others. This situation makes using the simplified approach highly unreliable. A large prediction gap with changing signs results in different comparison results from the reference method. As evident, method M3 makes only eight similar comparisons as method M1, out of 20. Moreover, most of the similar comparison results suggest no difference between the energy performance of the options.

Use of the ML model instead of dynamic simulations to make energy prediction is beneficial to reduce the computational time. However, the ML model also causes a prediction gap. In the presented test case, this gap widens up to only 0.9 MWh/a, which is the lowest among the three methods using the alternative approaches. Moreover, this prediction gap does not affect the results of comparing design options.

A plugin has been developed for BIM modelling tool to make BPS results available to the designer without remodelling efforts. For any of the methods, the designer need not spend time to remodel the information which is already present in the BIM model. So, the modelling time is exceptionally minimal and represents the time required by the plugin to generate data for simulations or ML predictions.

Further, the plugin is used to test the time-efficiency of the developed methods. Besides the accuracy of comparison results, the time-efficiency is one of the essential aspects in selecting an alternative approach. We are treating method M1 again as the reference method as modelling and prediction time required by this method will be the highest. In comparison, the deterministic approach requires very less modelling and prediction time as it requires only one simulation. However, utilising the threshold set by an expert, it makes the same comparison results as method M1. Method M3 requires 37% less modelling time and 68% less prediction time. However, it has a large prediction gap which results in different comparison results from the reference method. Method M4 requires very less time for modelling and prediction and compare design options without relying on the expert. Same as method M2, this method has all the comparison results the same as the reference method.

Looking at the results of comparing design options and time-efficiency, method M4 appears to be a promising development. This method utilises the probabilistic approach to treat uncertainty, detailed approach to create zones, and ML model to make energy prediction. However, it should be noted that the ML model has several limitations, for both its use and accuracy. The ML model used in this article are only tested for an office building with recti-linear floor plans, and weather data of Munich. However, researches have been done to train the ML model for the different weather data, too. More limitations on the values of parameters are documented in Appendix 2. The use and accuracy of the ML model must always be interpreted with the relevant details of data which is used to train and test the model. In the given context, the ML model offers flexibility for different recti-linear floor plans and the range of the parameters mentioned in Appendix 2.

Moreover, a designer needs to assess the design options based on several competing criterion such as structural performance, aesthetics and many more parameters. This article presents the only approach to assess the options based on their energy performance. However, the designer will assign suitable weightage to various performance criterion based on the project requirements and decide to select an option for further design development.

6. Conclusions

The researchers have presented four methods to make energy prediction and compare design options at the early design stage. One state-of-the-art approach and one alternative approach is selected to address the issues of uncertainty, zoning and computational time. The reference method uses a state-of-the-art approach to treat all the issues. The objective of reducing computational time requires an alternative approach of deterministic predictions, simplified zoning or machine learning-based energy prediction. Using a deterministic approach needs an expert to make comparisons; however, it provides reliable results for comparing design options. It can be used to obtain BPS results in extremely time-constraint situation. Using a simplified model approach should be avoided as it has a large prediction gap and fails to provide the same comparison results as the reference method. Machine learning-based energy prediction approach is time-efficient which uses pre-trained models to make energy predictions. This approach makes predictions for several design combinations within a few minutes. The small prediction gap using this alternative approach makes the comparison results as reliable as dynamic simulations. However, the training time, data requirement and limitations of machine learning model need to be assessed. In conclusion, the time-constraint situation of early design stage requires BIM integrated machine learning model to provide useful building performance simulation results for energy-efficient building design. The future research works should focus on overcoming the limitations of machine learning models and their seamless integration with BIM to provide quick, reliable, and comprehensive BPS results.

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Appendix 1: Validation of EnergyPlus Model for Early Design Stage

To validate the developed EnergyPlus (EP) model, we used the energy data of a medium-sized office building, Tausendpfund. This building is located in Regensburg, near Munich, Germany. Thus, we used weather data of Munich for validation purpose. The heating and cooling energy requirement for two years 2017 and 2018 are measured. The details of the building and the corresponding developed BEM has been provided in the following text.

1. Details of building

The building has a rectangular floor plan with external dimensions $14.7\text{m} \times 27.0\text{m} \times 9.75\text{m}$. This building has the same floor plan for each floor and has a total area of 1200 m^2 . In actual building, only 725 m^2 (60%) space is used as office space; the remaining part is accounted for walls, corridor and service spaces. A simplified thermal zone model is presented in Figure 9. Since, we are validating the model for the early design stage, instead of using actual thermal zone divisions, we used core and perimeter zone division with a perimeter depth of 4.5 m . This exercise resulted in five zones (four perimeter zones and one core zone) on each floor.

Figure 9. Simplified thermal zone floor plan of Tausendpfund building

1.1 Measured design parameters

The measured design parameters are building geometry, window area and u-values of the building envelope as described in Table 8. The u-values of walls, ground floor and roof are measured based on the thickness of each material layer and its thermal conductivity. The windows consist of a plastic frame and triple-layered glass. The floor slabs have a structural layer of reinforced cement concrete, having a heat capacity of 800 J/kg K . The window-to-wall ratio is 0.33 for all the directions. The building system has a heat pump to provide heating and cooling with coefficients of performance (COP) of 2.8 (heating) and 3.6 (cooling). In the winter season, additional heating is provided by a boiler which has an efficiency of 0.95.

Table 8. Measured design parameters

	Parameter	Unit	Value
Building Geometry	Floor Plan	-	Rectangular
	Length	m	14.7
	Width		27
	Floor-to-Floor Height		3.25
	No. of Floors	-	3
	Orientation	CW from North	20
Technical Specification	u-value	Walls	0.18
		Ground floor	0.19
		Roof	0.15
		Windows	0.87
	g-value	-	0.35
Window Construction	Window-to-wall ratio	-	0.33
System Efficiency	Heat Pump COP (Heating)	-	2.8
	Heat Pump COP (Cooling)		3.6
	Boiler Efficiency		0.95

1.2 Approximated or assumed design parameters

There are a few parameters which are difficult to be measured, such as infiltration. Besides these parameters, some parameters are fluctuating based on the building operation such as occupancy and light heat gains etc. We have taken either an approximate value of these parameters based on the national standard DIN 18599 or made reasonable assumptions. The details of these parameters are listed in Table 9.

Table 9. Approximated and assumed design parameters

	Parameter	Unit	Value
Technical Specification	Infiltration	ACH	0.3
	Internal Mass	kJ/Km ²	120
Operational Design	Light Heat Gain	W/m ²	6
	Equipment Heat Gain		12
	Occupancy	m ² /Person	24
	Operating Hours	Hours	11
Set Point	Heating Set Point	°C	20
	Cooling Set Point		25

We considered infiltration rate of 0.2 air changes per hour (ACH) for Category-II construction and addition 0.1 for windows as per DIN-18599 standard. The additional heat capacity of furniture is assumed to be 30 kJ/Km² for a medium-furnished office. The light requirement is approximated based on the illuminance requirement of 500 lux, assuming that it is provided using indirect LED lamps. An approximate equipment heat gain is 12 W/m². Both light and equipment heat gains are reduced to 10% during non-working hours. The building is assumed

to be operated for 11 hours a day with around 50 persons (24 m²/person) occupying the building during working hours. The heating setpoint is 20°C, and the cooling setpoint is 25°C. The setback temperatures are 15°C (heating) and 30°C (cooling). We assume natural ventilation by opening windows as the temperature is more than 23°C but less than 25°C.

2. Comparison of simulated and actual energy consumption

Figure 10 presents the simulated and actual energy consumption of the building. The simulated energy consumption of the building is 44.3 MWh/a. The significant portion of this energy is required for heating, i.e. 36.3 MWh/a (82%) and only 8 MWh/a (18%) for cooling. In the year 2017, the energy requirement is 42.08 (36.4 heating + 5.7 cooling) MWh/a which is around 5.1% less than the simulated value. In the year 2018, the energy requirement is 45.9 (36.2 heating + 9.7 cooling) MWh/a which is around 3.5% more than the simulated value. On average, the actual energy consumption is 43.97 MWh/a, which is 0.8% less than the simulated value.

Figure 10. Comparison of simulated and actual energy consumption

There is no data available for lighting energy consumption. The simulation data suggest an approximate energy requirement of 21 MWh/a for lighting, which translates to an annual electrical consumption of 18 kWh/m². In total, the building requires 65.3 MWh/a for providing heating, cooling and lighting which corresponds to annual energy consumption of 54 kWh/m². EnergyPlus model used for validation is available on Mendeley datasets - M.M. Singh, Validation of Early Design Stage EnergyPlus Model for Office Building, (2020). <https://doi.org/10.17632/x6xwvb2r9r.1>.

Appendix 2: Accuracy of Machine Learning Models (Verification)

The machine learning model used in this article has been developed as a component-based machine learning model (CBML), proposed by Geyer and Singaravel (2018) and developed further by Singh et al. (2019). The results of machine learning (ML) predictions are verified against the simulation data obtained from the reference EnergyPlus (EP) model. We have tested the accuracy of ML predictions on a combination of random building shapes (Figure 11) and the design parameters (mentioned in Table 10). The randomness of building shapes and design parameters ensures the applicability of verification results on the similar building configurations.

Figure 11. Random building shapes used to test the accuracy of ML predictions

A total of 3000 building samples are used for training ML models and 1000 test samples for testing ML models. This energy requirement includes energy for heating, cooling and lighting. The accuracy of ML predictions is presented using a scatter plot in Figure 12. The developed model shows an accuracy of 0.94 in terms of R^2 and root mean square error (RMSE) of only 4.2 MWh/a.

Figure 12. Accuracy of ML prediction with reference to EP simulation

Table 10. Details of design parameters to test the accuracy of ML predictions

	Parameter	Unit	Range
Building Geometry	Floor Plan	-	Random
	Total Floor Area	m ²	(400, 2000)
	Floor-to-Floor Height	m	(3, 4)
	No. of Floors	-	(2, 4)
	Orientation	CW from North	(0, 45)
Technical Specification	u-value	Walls	(0.1, 0.3)
		Ground floor	(0.1, 0.3)
		Roof	(0.1, 0.3)
		Windows	(0.6, 1.2)
	g-value	-	(0.15, 0.65)
	Infiltration	ACH	(0.15, 0.45)
	Internal Mass	kJ/m ²	(15, 45)
Window Construction	Window-to-wall ratio	-	(0.2, 0.8)
System Efficiency	Heat Pump COP (Heating)		(2.5, 3.5)
	Heat Pump COP (Cooling)	-	(3.5, 4.5)
	Boiler Efficiency		(0.86, 0.98)
Operational Design	Light Heat Gain	W/m ²	(3, 9)
	Equipment Heat Gain		(8, 16)
	Occupancy	m ² /Person	(15, 25)
	Operating Hours	Hours	(8, 14)

The developed ML model is limited to the simulation data which is used to generate the training and test dataset. Thus, the results must be interpreted within the context of the simulation model. Some limitations of the simulation model are:

1. It utilises the weather data of Munich; thus, the model is only applicable for the location of Munich.
2. The simulation model considers a typical operation of the office building. To use ML model for other building type requires additional work.
3. The simulation model considers the effect of self-shading only. The effect of surroundings or overhangs is not modelled.

The data used for testing ML model is available on Mendeley datasets - M.M. Singh, Verification of Early Design Stage Machine Learning Model using EnergyPlus Simulation Data, (2020). <https://doi.org/10.17632/ms56cbx7dy.1>.