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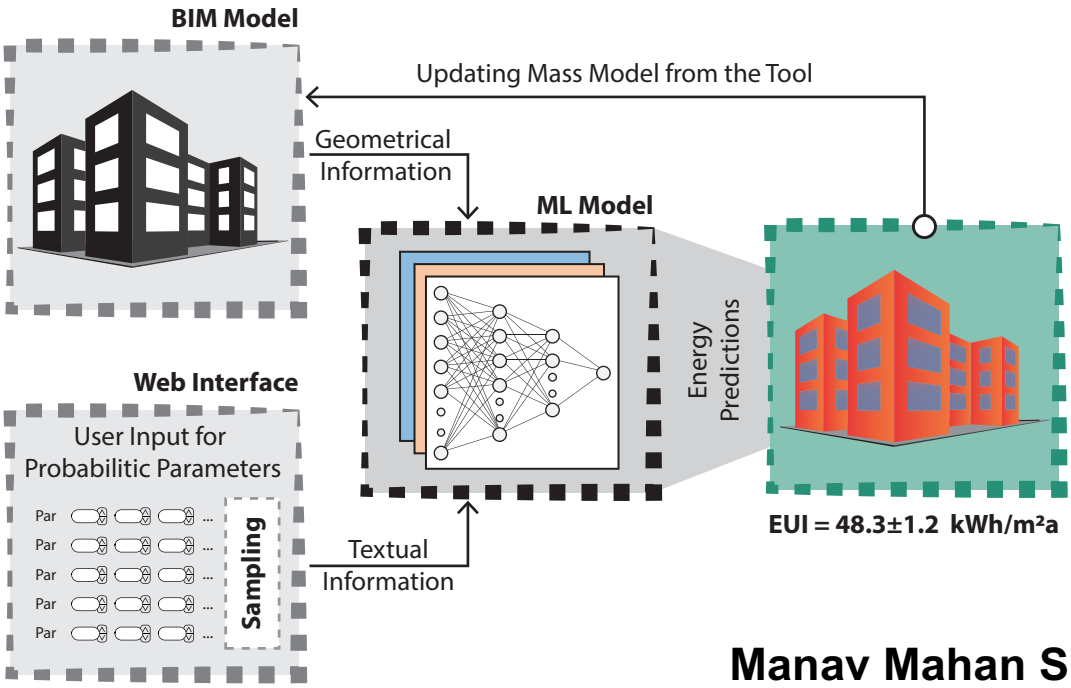
FACULTY OF ENGINEERING SCIENCE

Early-stage design support using machine learning and building information modelling



Manav Mahan Singh

Supervisor(s):
Prof. dr. ir. Krista De Jonge
Prof. dr. ir. Ralf Klein
Prof. dr. ir. Philipp Geyer

Dissertation presented in partial fulfilment of the requirements for the degree of Doctor of Engineering Science (PhD): Architecture

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EARLY-STAGE DESIGN SUPPORT USING MACHINE LEARNING AND BUILDING INFORMATION MODELLING

Manav Mahan SINGH

Supervisor(s):
Prof. dr. ir. Krista de Jonge
Prof. dr. ir. Ralf Klein
Prof. dr. ir. Philipp Geyer (LU Hannover)

Members of the Examination Committee:
Prof. dr. ir. Jean Berlamont (Chairman)
Prof. dr. ir. -arch. Karen Allacker
Prof. dr. ir. -arch. Dirk Saelens
Prof. dr. ir. André Borrmann (TU Munich)
Prof. dr. ir. Jakob Beetz (RWTH Aachen)

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The greatest threat to our planet is the belief that someone else will save it!

- *Robert Swan*

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- Manav Mahan Singh

Summary

Buildings represent one-third of energy consumption that concerns the global community. During the early design stages, designers have an opportunity to improve the energy performance of buildings efficiently. However, they need information to assess the effect of their design decisions on the energy performance. The doctoral research developed methods to support energy-related design decisions at the early stages using machine learning (ML) and building information modelling (BIM) by providing relevant information.

The flexible representation of design at the early stages is a prime challenge to assess energy performance and the effect of design decisions on it. This challenge is addressed using a probabilistic approach that requires simulating several hundred models. Dynamic energy simulation tools are computationally expensive, prompting the development of quick metamodels using ML approaches. Further, a BIM integrated approach is developed to reuse the existing information and reduce the modelling efforts.

The building design progresses by developing information through several levels of development (LOD). While focussing on energy efficiency, it is apt to reduce uncertainty in energy predictions through these LODs. Thus, the research identified design information in the order of its potential to cause uncertainty in the energy predictions. It has been found that geometrical parameters cause the maximum uncertainty in the energy predictions, followed by technical specifications such as U-values and window parameters such as window-to-wall ratio. These results form the basis for design information required in a multi-LOD context.

The research further developed metamodels using ML for quick energy predictions, primarily, focussing on evolving building geometry, making it difficult to develop an ML model for early stage energy predictions. It extended the component based ML (CBML) approach and proposed using a convolutional neural network (CNN) approach to develop ML models. An approach of collecting diverse samples is developed to train CBML components and improve their generalisation. A CNN approach is used to capture the building geometry information from an image instead of simple parameters such as relative compactness. The developed model has improved prediction accuracy as the proposed CNN model architecture allows learning the interactions between the building's geometry and its energy performance.

There exists a prediction gap between ML predictions and dynamic simulations. A small prediction gap is allowed if it does not affect the comparative assessment of designs under the uncertain conditions of early design stages. Through a test case, the research demonstrated that the developed ML models are suitable to perform a comparative assessment of designs quickly. The aptness of ML models to provide quick comparative assessment of designs allows developing a BIM integrated solution and glean relevant information for supporting design interventions. In the final phase, a cloud based service was developed: p-energyanalysis.de. It

implements the developed ML models in a graphical user interface for practical applications. The tool provides information for design space exploration, energy analysis of options and their comparative assessment, sensitivity analysis, and tracks progress. Contrary to generic engineering knowledge, the developed tool extracts context-specific energy performance information. This information is more relevant as it captures the effect of changing design scenario on the energy-efficiency.

The thesis facilitates the performance-oriented building design by providing relevant information using ML and BIM. The developed methods focus on informed design making from an energy perspective that can be extended to other performance evaluations. Besides developing ML models for energy prediction, this research integrates these models with BIM to extract useful information for supporting design interventions. The developed holistic approach provides a quick context-specific assessment of design interventions that enables the designer to make informed decisions.

Samenvatting

Gebouwen zijn verantwoordelijk voor een derde van het energieverbruik wereldwijd. Tijdens de vroege ontwerpfasen hebben ontwerpers de mogelijkheid om de energieprestaties van gebouwen efficiënt te verbeteren. Zij hebben echter informatie nodig om het effect van hun ontwerpbeslissingen op de energieprestatie te beoordelen. Daarom werden in deze doctoraatsthesis methoden ontwikkeld om energiegerelateerde ontwerpbeslissingen tijdens deze fase te ondersteunen door gebruik te maken van machine learning (ML) en building information modelling (BIM) om relevante informatie te verstrekken.

Een variabele voorstelling van het ontwerp in een vroeg ontwerpstadium is een belangrijke uitdaging om de energieprestaties en het effect van ontwerpbeslissingen daarop te beoordelen. Deze uitdaging wordt aangepakt met een probabilistische aanpak die de simulatie van enkele honderden modellen vereist. Dynamische energiesimulatietools zijn rekentechnisch duur, wat ertoe leidt dat snelle metamodellen moeten worden ontwikkeld met behulp van ML-benaderingen. Daarenboven wordt een geïntegreerde BIM-aanpak ontwikkeld die bestaande informatie kan hergebruiken en zo de inspanningen voor energiemodellering kan verminderen.

Het ontwerp van een gebouw vordert door informatie te ontwikkelen via verschillende ontwikkelingsniveaus (Levels Of Development, LOD). Naast de focus op energie-efficiëntie, is het aangewezen om de onzekerheid in de energievoorspelling via deze LOD's te verminderen. Deze studie identificeerde ontwerpinformatie volgens hun potentieel om onzekerheid in de energievoorspellingen te beïnvloeden. Geometrische parameters blijken de grootste onzekerheid te veroorzaken in de voorspelling van de energieprestatie, gevolgd door technische specificaties zoals u-waarden en andere parameters zoals de window-to-wall ratio. Deze resultaten vormen de basis voor de ontwerpinformatie die nodig is in een multi-LOD context.

In een volgende stap werden in deze studie metamodellen ontwikkeld met behulp van ML voor snelle energievoorspellingen. Deze studie richt zich op veranderende gebouwgeometrie die het moeilijk maakt om een ML-model te ontwikkelen voor energievoorspellingen in een vroeg stadium. De component-gebaseerde ML (CBML) benadering wordt uitgebreid en er wordt voorgesteld een convolutional neural network (CNN) te gebruiken om ML-modellen te ontwikkelen. Er wordt een aanpak ontwikkeld waarbij diverse modellen worden verzameld om CBML-componenten te trainen en hun generalisatie te verbeteren. Er wordt een CNN-benadering gebruikt om de geometrische informatie van een gebouw uit een beeld te halen in plaats van eenvoudige parameters zoals relatieve compactheid te gebruiken. Het ontwikkelde model heeft een verbeterde voorspellingsnauwkeurigheid omdat de voorgestelde CNN-modelarchitectuur het mogelijk maakt de interacties tussen de geometrie van het gebouw en zijn energieprestaties te leren.

Er bestaat een voorspellingskloof tussen ML voorspellingen en dynamische simulaties. In de context van deze studie is een kleine voorspellingskloof toegestaan als die geen invloed heeft op het vergelijken van ontwerpen onder de onzekere omstandigheden in een vroege ontwerpfase. Door middel van een testcase heeft deze studie aangetoond dat de ontwikkelde ML modellen geschikt zijn om snel een vergelijkende beoordeling van ontwerpen uit te voeren.

De toepasbaarheid van ML-modellen voor een snelle vergelijkende beoordeling van ontwerpen maakt het mogelijk een in BIM geïntegreerde oplossing te ontwikkelen om relevante informatie te verzamelen ter ondersteuning van ontwerpinterventies. In de laatste fase van dit onderzoek werd een cloud-gebaseerde dienst ontwikkeld: p-energyanalysis.de. Het implementeert een grafische gebruikersinterface voor de praktische toepassing van de ontwikkelde ML-modellen. De tool biedt informatie voor verkenning van de ontwerpruimte, energieanalyse van een ontwerpoptie, vergelijking van verschillende ontwerpopties en gevoeligheidsanalyse en houdt de voortgang bij. In tegenstelling tot generieke ingenieurskennis onttrekt het ontwikkelde instrument context specifieke energieprestatie-informatie. Deze informatie is relevanter omdat zij het effect van een veranderend ontwerpscenario op de energie-efficiëntie vastlegt.

Deze thesis vergemakkelijkt het prestatiegericht ontwerpen van gebouwen door het verstrekken van relevante informatie met behulp van ML en BIM. De ontwikkelde benaderingen richten zich op geïnformeerde besluitvorming vanuit een energieperspectief dat kan worden uitgebreid naar andere prestatie-evaluaties. Naast het ontwikkelen van ML modellen voor energievoorspelling, integreert deze studie de modellen met BIM om nuttige informatie te extraheren voor het ondersteunen van ontwerpinterventies. De ontwikkelde holistische benadering biedt een snelle context specifieke beoordeling van ontwerpinterventies die de ontwerper in staat stelt weloverwogen beslissingen te nemen.

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List of Abbreviations (alphabetically)

ACH	Air Changes per Hour (unit of infiltration)
BEM	Building Energy Model
BDL	Building Development Level
BEM	Building Energy Model
BIM	Building Information Modelling
BPS	Building Performance Simulation
CBML	Component based Machine Learning
CI	Confidence Interval
CNN	Convolution Neural Network
COP	Coefficient-of-performance
CPU	Central Processing Unit
DL	Deep Learning
EE	Embedded Energy
EHG	Equipment Heat Gain
EnEV	Energieeinsparverordnung (Energy Saving Ordinance)
EUI	Energy Use Intensity
GHz	Giga Hertz (unit of CPU frequency)
g-value	Solar heat gain coefficient
IFC	Industry Foundation Classes
kWh	kilo-Watthour (unit of energy)
kWh/a	kilo-Watthour per annum (unit of energy use per year)
kWh/m^2a	kilo-Watthour per square metres per annum (unit of EUI)
LHG	Light Heat Gain
LOD	Level of Development
$m^3/h.m^2$	Cubic meters per hour per square meters (unit of air permeability)

MAE	Mean-Absolute-Error
MAPE	Mean-Absolute-Percentage-Error
MJ	Mega Joules (unit of total energy)
ML	Machine Learning
MWh	Mega-Watthour (unit of total energy)
OE	Operational Energy
PCA	Principal Component Analysis
R^2	Coefficient of determination / goodness-of-fit
RIBA	Royal Institution of British Architects
RMSE	Root Mean Square Error
RSL	Reference Service Life
SRC	Standardised Regression Coefficient
U-value	Thermal transmittance
WWR	Window-to-Wall Ratio
W/m^2K	Watt per square metre per kelvin (unit of U-value)

1

Introduction and background

Chapter 1.
Introduction and background

A built environment is designed to provide a safe, comfortable, and conducive atmosphere for work, education, recreation, or other activity. One of the essential characteristics of buildings is the thermal comfort that affects its users' productivity [1,2]. Physically, the thermal condition of a built environment can be described by air temperature, radiant temperature, humidity, and air velocity [3]. Various standards define the thermal comfort criteria for a built space based on its purpose. The thermal comfort is achieved using different energy systems. For example, it may use gas to heat water that is used to heat the air through convective heating or chilled water may be used to cool floor slabs. However, all energy systems require energy that concerns the global community.

Various reports suggest that buildings are the major energy consumers. Buildings use around 40% of the total energy in the European Union [4]. In developed countries, buildings account for 20-40% of the total energy consumption, more than any other sector. In 2004, globally, buildings consumed around 24% of the total energy [5]. Moreover, non-residential buildings in the European Union have an energy consumption of around 250 kWh/m^{2}a, 40% more than the residential buildings [6]. Our planet is continuously losing valuable energy resources to make buildings more comfortable for human activity. The global community is getting more concerned about global warming issues and looking forward to promoting sustainable development. Following the community aspirations, statutory authorities are also promoting green energy solutions through various incentives. Some of these incentives are energy efficiency obligations, energy tax, fiscal incentives, low-cost finance for the green energy systems, and standards [7].

Architects and engineers play a significant role in the sustainable development of built environment sector; but there is always a question 'how' (Figure 1.1). One common approach is to use efficient systems to minimise the energy needs. Another approach is on-site power generation such as photo-voltaic panels or wind turbines. Most countries implemented these systems and yielded good results with a slight disadvantage of high initial cost. Smart building solutions also present a good prospect of making the existing system energy-efficient by

optimising its operation [8]. Besides these approaches, there exists another significantly cost-efficient approach, i.e., designing an energy-efficient building envelope [9]. A designer develops essential characteristics of a building envelope at early design stages that have significant influence on its energy performance. Thus, a better energy performance can be achieved at a lower investment cost by designing an efficient building envelope from the early stages. However, it is not easy to design energy-efficient from the beginning as it requires a lot of experience to do everything right from the start. The following sections provide more context to the challenges of designing energy-efficient buildings from the early stages.

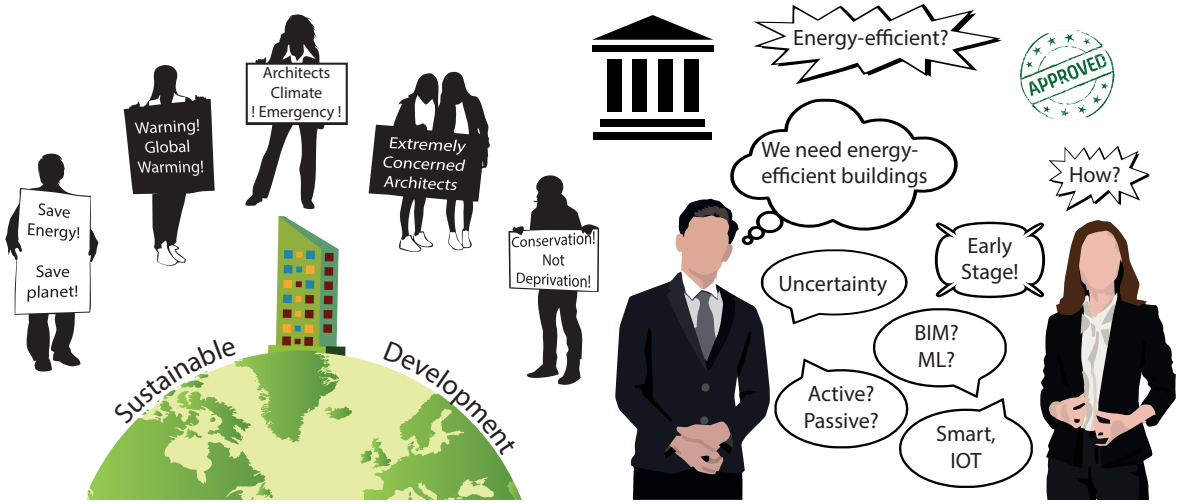


Figure 1.1 We need energy-efficient buildings; but, how?

1. Early stages in building design context

Building design is an iterative and evolutionary process [10], in which designers experiment with various design solutions. In this iterative process, building's performance is assessed based on many performance criteria to make decisions at any stage. Once an optimal design is found, some features are finalised and the design progresses to the next stage. Hence, referring to the early design stages means only few features are finalised and many features are flexible. The flexible design features are important to improve the energy performance at a lower cost.

Early stages refer to all the design stages before the detailed design. Thus, at early stages, designers develop building mass, indicative area/volume, location, orientation, and generalised building systems, including non-geometrical properties. Figure 1.2 shows two early design stages. A designer develops conceptual design at Stage 1, i.e., the mass model showing indicative area, volume, and orientation. Based on multidisciplinary performance analysis, some features are finalised and design progresses to Stage 2. At stage 2, designers develop preliminary design, i.e., internal spaces, fenestration, generalised building system. For example, wall will have medium insulation and fenestration will have low U-value and high g-value. At a higher stage, more details are developed and maturity in the design information improves. Considering the RIBA plan of works, stage 1: preparation and briefing, stage 2: concept design,

and stage 3: spatial coordination, may be considered as the early design stages [11]. From Singapore's building and construction authority perspective, conceptual design and schematic/ preliminary design are the early design stages [12]. Generally, building design is treated as a linear process [13]; however, most design activities are interrelated, meaning design features that are finalised at any stage are subject to change at later stages [14]. This step is considered as retracting to the previous stage, as shown in Figure 1.2. For consistency, the thesis refers to a design stage as a level of development (LOD).

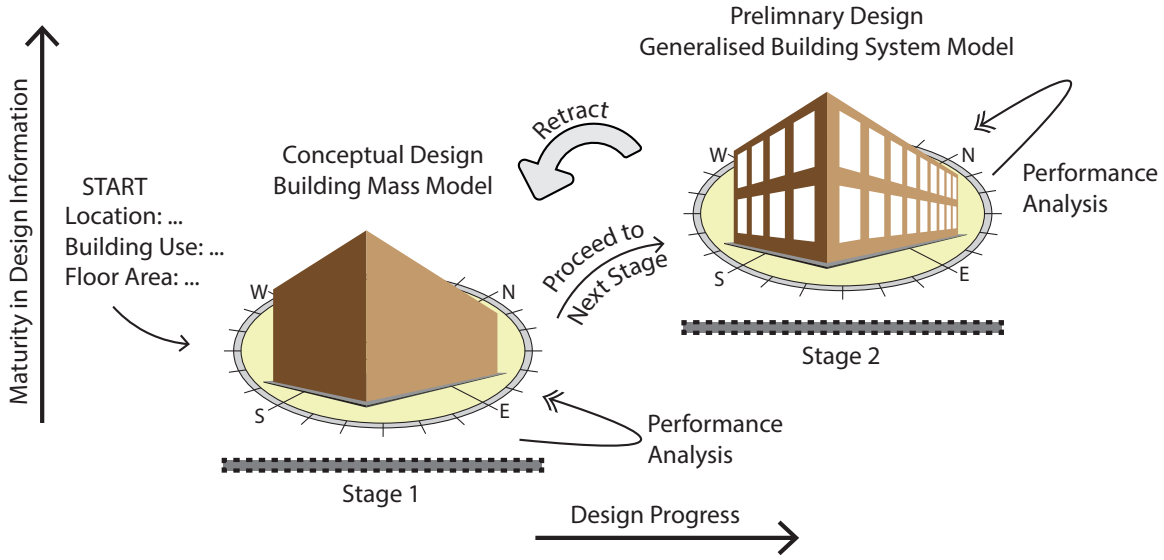


Figure 1.2 Illustration of early design stages in building design context

The evolutionary and iterative nature of the design requires switching between LODs [15,16]. The multi LOD concept suggest that the design information is stored at different LODs in a single model that allows switching among different LODs. The multi LOD approach overcomes several challenges of the traditional design process [17]. Initially, all the design parameters are defined with uncertainty, i.e., a parameter is defined by a possible range of values, discrete values, or mean value with a statistical distribution [18]. As the design progresses, some parameters are focussed and finalised at each LOD. Hence, the multi LOD approach allows designing the building with flexibility [19].

2. Performance-oriented building design

It is a design paradigm in which buildings are designed to meet measurable or predictable performance requirements without explicitly prescribing the method. The performance requirement depends on the users' needs, aspirations, and desires, such as energy-efficient, earthquake-resistant, or low-cost design. It must be noted that only part of the user requirements relates directly to the building performance [20]. The performance criteria are derived by translating users' requirements into measurable physical values. For example, in the sustainable development context, the building's life cycle energy is measured by the total energy

requirement per unit of floor area or global warming potential. These measurements allow comparing the proposed design solutions with the existing building stock or other solutions.

In the energy-efficient design context, the objective is to achieve low energy use and promote on-site or renewable energy generation; however, specific details are under the designer's prerogative. Figure 1.3 shows typical activities of performance-oriented design in a uni-disciplinary approach. The first task is to define a measurable performance criterion for the low energy under a wider requirement to design energy-efficient buildings. It requires a performance measure to define energy efficiency that can be expressed as energy use intensity (EUI) [21] or other measures such as carbon footprint, global warming potential or CO_2-equivalent. It is followed by setting up a performance criterion such as EUI must be less than 75 kWh/m^{2}a. The criterion depends on the performance of the existing building stock, building standards, or future technologies. The subsequent tasks are designing the building, evaluating its performance, and making changes to achieve the performance criteria. In these tasks, two tasks are of prime importance that require developing novel tools and methods:

1. Evaluate the design – design solutions need to be evaluated using a performance assessment tool. It can be performed using the rules-of-thumb, steady-state heat transfer equations, dynamic simulations, or machine learning (ML) models. However, it must be noted that it should be quick, reliable, and adapt to design changes.
2. Make changes – designers should be provided with the information to make necessary changes in the design to achieve the performance criteria. Designers should have information about the effects of design changes on the building's energy performance.

Regulatory frameworks through energy performance standards play a crucial role in determining building requirements. These frameworks define the requirements for different building systems, including energy. Since climate, location, size, and use greatly affect building's energy performance, a common performance criterion cannot be applied to all buildings. Most energy standards have been developed to meet regional requirements. In the simplest form, it can be tabulated values that prescribe the performance value for each building component. For example, the U-value of walls must be lower than 0.35 W/m^{2}K or the boiler must have an efficiency of 0.92 or higher. The standards can also define the overall performance criteria, such as the energy use intensity of the building should be lower than 75 kWh/m^{2}a. In more complex terms, the standard can define that the building should have energy use less than the reference building that has been designed according to the standards [22]. Moreover, these performance based standards aim to assess the energy-saving potential of the building with reference to the prescribed value using an engineering approach [23].

Building design is a multidisciplinary process that requires evaluating a design solution based on several performance criteria such as structural, construction cost, embedded energy etc. For a simplified definition, Figure 1.3 shows only uni-disciplinary approach for the energy use.

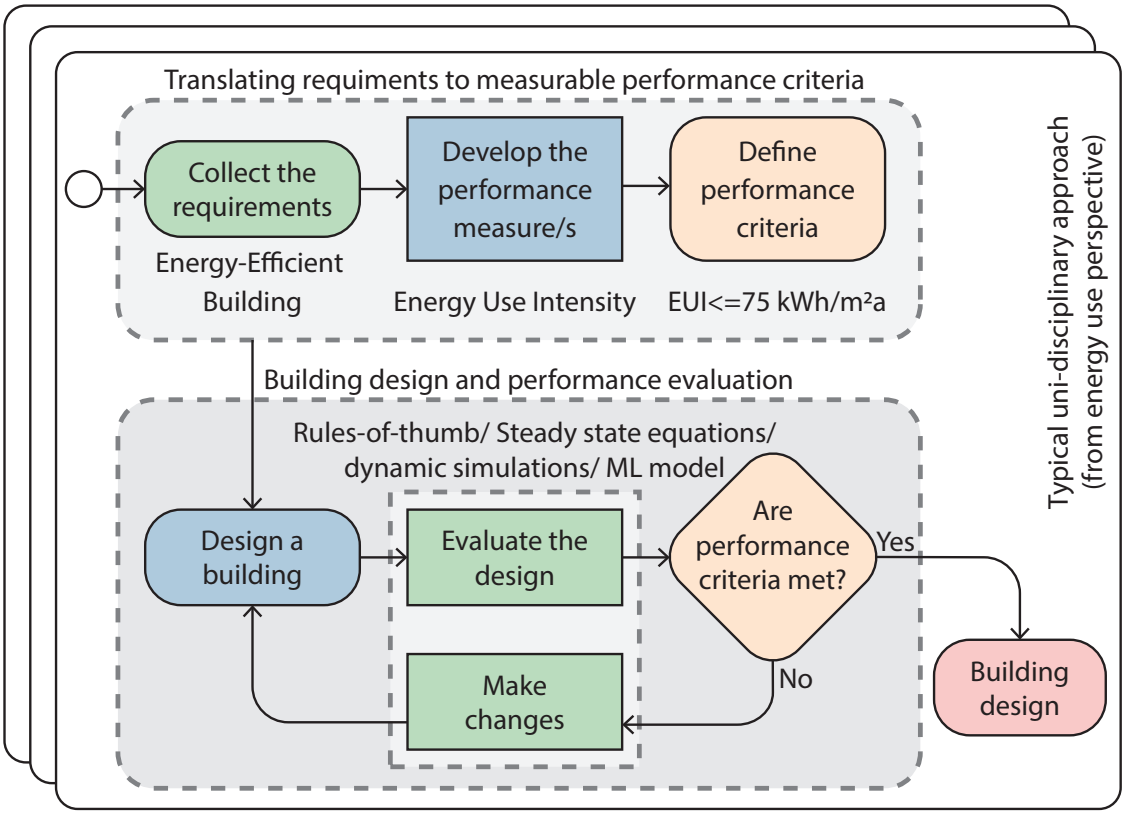


Figure 1.3 Typical performance-oriented building design (uni-disciplinary)

3. Challenges and state-of-the-art approaches to early stage energy prediction

Predicting energy demand is one of the important prerequisites to assess the effects of design decisions and make informed choices. Moreover, it requires predicting the performance of the current and potential design solutions to provide relevant information for decision-making. By comparing the performance of various designs, designers can make an informed choice for further development. Flexible design definition is essential to efficiently improve the performance. However, it brings several challenges to predict the energy performance. The following subsections discuss the challenges to early stage energy prediction and state-of-the-art approaches to overcome these challenges:

3.1 Uncertainty in the design information

Early stages are characterised by inherent uncertainty in the design information [24]. Building systems are described in generic terms to achieve a certain performance [25]. Such as, external walls will be brick construction with medium insulation to achieve a U-value of 0.2 W/m^{2}K, or there will be 40% windows on north walls with double glass panes with a U-value of 1.5 W/m^{2}K. The generic definition of building systems with a targeted performance requirement introduces uncertainties in its thermal behaviour. For example, a double glass pane window can have an U-value of 1.1-2.8 W/m^{2}K [26,27] and its exact value depends on the decisions made at later stages. Nevertheless, an effective U-value for windows is the weighted sum of the solid

portion (frame) and the transparent glass pane that adds more uncertainty. The heat transfer calculations through building elements are more uncertain, given additional deviation in the thermal behaviour due to workmanship on the site [28]. Likewise, building airtightness is set as a requirement but cannot be estimated during the design. German standards classify four categories of construction to estimate the air permeability during design [22]. It specifies the maximum air permeability of 6 m^3/m^2h for type-II construction that can be as low as 3 m^3/m^2h. However, the airtightness can only be measured by a fan-pressurisation method after the construction [29]. These are some reasons for a high uncertainty in the design information at the early stages.

Some parameters are uncertain even during the operational phase of the building lifecycle, with a high potential to influence its energy performance. Some of these parameters relate to building operation, such as the number of occupants, light and equipment heat gains, and hours of operation. During the design phase, an energy analyst makes suitable assumptions based on the standards and available data to estimate these parameters. Realistic assumptions are required to minimise the gap between the simulated energy performance and the actual performance. Some parameters, such as the performance coefficients of energy systems depend on the outside conditions that require advanced methods to estimate their value [30]. It is neither advisable nor possible to predict precise energy demand with so many uncertainties in the design information at the cost of expensive modelling and computational efforts. Hence, at the early stages, BPS results are used to compare and classify design options than predicting the energy performance [31].

Previously, researchers suggested probabilistic approaches to address the inherent uncertainty at the early stages [24,28]. An uncertain parameter is defined by a range of possible values. The approach of probabilistic energy predictions samples uncertain parameters from the possible values to create several energy models. The energy models are simulated to predict a range of possible values for the energy demand. Since the energy demand is defined by a range of possible values, it is more difficult to understand probabilistic predictions than deterministic (one-point) predictions. Hence, statistical methods are required to compare design solutions based on the probabilistic energy performance. For example, the Wilcoxon rank-sum test can be used to determine the probability of one option being better than the other under given uncertain conditions. Another utility of BPS is to assess the effect of a parameter on the energy performance. In a deterministic approach, the effect is assessed by the ratio of change in the parameter value and corresponding change in the energy performance. This approach does not consider the effect of interactions among the parameters. Global sensitivity analysis methods, such as the Morris method, regression, or variance based methods, are required to capture the effect of parameters' interactions and higher-order effects [32]. Thus, the inherent uncertainty at the early design stages requires simulating several energy models to obtain probabilistic BPS results. Further, it requires statistical tools and global sensitivity analysis methods to process probabilistic BPS results and extract meaningful information to support decision-making.

3.2 High computational time

Energy performance assessment during the design phase is performed using sophisticated simulation tools such as EnergyPlus [33], ESP-r [34], or TrnSys [35]. Researchers have also developed libraries to simulate the energy performance using Modelica [36,37]. Dynamic simulation tools offer a very high degree of accuracy and represent the state-of-the-art solutions to predict energy demand during the design. Dynamic simulations are performed by solving heat and mass transfer equations with a time resolution as small as a minute. In most cases, hourly simulations are sufficient to achieve reasonable accuracy for calculating yearly energy demand. However, an hourly simulation also requires calculations to be carried out at 8760 timesteps (number of hours in a year) and takes around 2-5 minutes to simulate a building energy model (BEM). The previous section illustrates that it requires simulating several energy models to provide information for decision-making at the early stages. If it requires around 200 samples to make probabilistic energy predictions, dynamic simulations will take 6-18 hours. Advanced computing resources can reduce this time to an hour using multiprocessing. For example, the same number of energy models can be simulated in 1-2 hours using an 8-core CPU, available with personal computers. Still, this time is higher than a designer can wait for BPS results at the early stages. Thus, the computational expensiveness of dynamic simulations prompts a question of their efficacy at the early stages.

Metamodels or engineering surrogate models are developed as time-efficient alternatives to expensive dynamic simulations [38,39]. Metamodels emulate physics based simulation model by approximating its behaviour, i.e., the relationship between the inputs (predictors) and the model outcome [40]. Assuming Eq. 1 represents a simulation model f(X) that models the relationship between the model outcome y and the predictors X. Eq. 2 represents a metamodel h(X) that approximates the behaviour of model f(X).

$$y = f(X) \qquad \text{... Eq. (1)}$$

$$y \approx h(X) \qquad \text{... Eq. (2)}$$

There are several approaches to develop metamodels that include regression, statistical approaches, and machine learning (ML) [41]. Among these approaches, ML has been used extensively because of its ability to capture the complex interactions of BEMs; hence, low prediction errors [42]. Reliable energy predictions require the gap between the ML predictions and the state-of-the-art dynamic simulations to be as ‘small’ as possible. A more elaborate definition of a ‘small’ prediction gap is provided in subsection 5.3.

ML approaches are highly reliant on the data used for training and testing the model; hence, any ML model has the constraint of the data. This constraint requires training and testing ML models for a specific purpose. Previously, researchers focussed on developing ML models for a wide range of technical specifications, with only a little importance given to the architectural

form [43]. Since the research focuses on the early stages that are characterised by the development of building mass and a wide range of technical specifications, building geometry has been given importance while developing ML models.

Generalisation is an important concept in developing ML models which is defined by the model's ability to accurately predict the energy demand outside the training cases [44]. The generalisation is estimated by the errors on a test dataset which has samples independent of the training dataset. Thus, a well-generalising ML model in the context of this research refers to an ML model that has low generalisation errors on a test dataset containing building samples of different shapes and a wide range of technical specifications. Even though if designers give less importance to energy performance while changing the building's geometry, an ML model that generalises well for different geometries is required to assess the effect of geometrical changes and compare it with other options.

Building shape is a complex feature to be represented by a set of parameters. The ML model structure needs to capture the interaction between the shape of building and its energy performance. Previously developed parametric ML modelling approaches capture the building shape by simple parameters, such as relative compactness [45] or shape factor [46]. However, a limited representation of building shapes in ML models leads to a loss of accuracy. [47] developed a component based machine learning (CBML) approach that decomposes building artefacts into smaller components, and the ML models predict the energy performance of these components. The energy performance of a whole building is predicted by arranging the required components. However, the approach shows a loss in accuracy when tested on complex building shapes. Thus, there is a need to develop a well-generalising ML model that can predict building energy performance at the early stages with a 'small' prediction gap.

Dr. Singaravel has worked extensively to develop well-generalising ML model for early stage energy predictions [44]. His research focussed on various ML and deep learning algorithms that have ability to capture complex interactions of building energy models [48]. His works also explained the ability of deep learning models to automatically learn building features compared to neural networks. Further, his works explained the well-generalising behaviour of the ML model on unseen design cases of different dimensions [42]. However, his research does not focus on building geometry and the model development was limited to box-shaped buildings.

Dynamic simulations use physics based models to estimate the building energy use. These white box approaches allow tracing the effect of inputs on the output through the equations. However, the approaches are very time consuming to be parameterised. In contrast, ML models solely rely on the data to model the input output relationship, representing a black box approach that requires advanced methods to explain their behaviour. Grey box modelling approaches represent a middle ground that are more interpretable than black box models and simpler than white box models [49]. In grey box approaches, the model structure is developed using the

domain knowledge and the parameters are trained on the data [50]. Resistance capacitance models are widely used to develop grey box models for building energy prediction [49]. Besides offering a better interpretation, grey box models do not offer much advantage over ML models. While ML models are developed solely based on the data, grey box models require the domain knowledge to develop the model structure. ML models can capture nuances in the data without changing the model structure. Moreover, researchers are developing methods to interpret the behaviour of ML models [44]. Thus, ML models are easy to develop and offer some interpretability in comparison to grey box approaches.

ML models are developed as a time-efficient alternative to dynamic simulations. It means ML models quickly predict energy demand for several models as required to address the uncertainty at the early stages. However, it requires some time and efforts to develop ML models for quick energy predictions. Developing an ML model requires collecting a considerable number of samples, followed by training and testing the ML model. However, once developed, the models quickly predict the energy use when designers are making changes to the design.

3.3 Expensive modelling efforts

Dynamic simulations require significant efforts to develop BEM. In a conventional approach of developing BEMs, energy specialists extract information from drawings and documents, followed by feeding the information to an energy simulation tool [51]. This approach of energy modelling has three major drawbacks:

1. Extracting, processing, and translating information for an energy simulation tool is time-consuming and requires significant remodelling efforts.
2. Any update requires developing a new model or updating the energy model that requires analysing the changes and updating the model, accordingly.
3. The conventional approach to develop BEM is prone to errors and requires experience.

Since the design is under development at the early stages, the BEM needs to be updated for design changes. If developing BEM is not automated, the energy assessment is not performed at intermediate stages, and BPS results are not available for decision-making. In such situations, the designer makes the subjective assessment of the design solution using the rules of thumb or experience. The expensive modelling efforts limit the use of BPS results to showcasing energy saving potential or preparing compliance reports rather than supporting design decisions [52]. Building information modelling (BIM) presents a promising prospect for continuously updating the energy model during design phase. Among many BIM definitions, the following suites the best in this context:

> *"BIM is a process for generating, storing, managing, exchanging, and sharing building information in an **interoperable** and **reusable** way."*
>
> *- BIM Handbook (Eastman et al.)* [53]

Researchers exploited information from the BIM model to create energy simulation model [54]. BIM information is translated using pre-defined rules to create BEM that minimises the modelling efforts. However, it requires designers to follow specific modelling guidelines to allow seamless translation. Some researchers integrated industry foundation classes (IFC) model with the dynamic simulation tool, EnergyPlus and developed an object library for Modellica [55–57]. These approaches allow continuously updating the energy performance results for design changes with minimal efforts.

The current approaches of BIM-BPS integration are used to make deterministic energy predictions by simulating one BEM. However, the early stages require simulating several energy models for predicting the probabilistic energy performance and decision-making. Section 3.2 discusses using the ML model instead of dynamic simulations to reduce the computational time. Hence, quick probabilistic energy predictions require integrating BIM and ML models. This integration requires new rules as the information needs to be translated according to the ML model structure. For examples, if an ML model uses the building dimensions, it will require to provide length, width, and height as numerical inputs. Similarly, if it uses building footprint, an image representing building footprint, needs to be generated. Hence, the current approaches to BIM-BPS integration need to be adapted for obtaining probabilistic BPS results using ML models. Further, it needs to be extended to extract the relevant information for making design decisions, using statistics and sensitivity analysis methods, as discussed in section 3.1.

4. Summary of knowledge gaps and scope of the research

There is a need to design energy-efficient buildings from the early stages. However, the flexible design representation poses several challenges to energy predictions at the early stages and prompts the designer to rely on conventional knowledge or generic rules-of-thumb. Previously, state-of-the-art approaches of probabilistic predictions, ML, and BIM integration have been developed to overcome the challenges of uncertainty, high computational time, and expensive modelling efforts, respectively. However, some limitations affect the use of BPS results for decision-making at the early stages. The following points summarise these knowledge gaps:

1. The multi LOD approach allows the flexible representation of design by defining the parameters with uncertainty that causes uncertainty in the predicted energy use. Designers focus on some parameters at each LOD and remove or reduce the uncertainty in these parameters, reducing the uncertainty in energy predictions. However, it lacks engineering knowledge to inform designers which parameters should be focussed at any LOD. From the energy perspective, designers need to prioritise the parameters in the order of their ability to cause uncertainty in energy predictions. The information (parameters to be focussed) that remove the maximum part of uncertainty in energy predictions at each LOD needs to be determined.

2. ML models are required to quickly predict the probabilistic energy demand under uncertain conditions of the early stages. Designers develop the building mass model and geometry with many uncertain parameters at the early stages. Hence, the previous approaches of ML model that are limited to few building geometries are unreliable to predict the energy demand of the early stage building configurations. ML models that generalise well for different building shapes and a range of technical specifications are required to evaluate the effect of early stage design decisions on the energy predictions.
3. The objective of energy predictions at the early stages is limited to compare and classify design options rather than making precise energy prediction. This objective allows 'small' errors in energy predictions so that it reduces the time to obtain the results but does not affect the decisions of comparing design options. ML models represent a deliberate trade-off between time and accuracy; hence, quick ML models can be used instead of dynamic simulation if there are only 'small' errors in predictions. However, there is no method to determine how much error should be considered 'small'; hence, the suitability of ML model cannot be ascertained for the early stage energy predictions.
4. Researchers developed methods to address various challenges to early stage energy prediction using probabilistic, ML, and BIM integration approaches. However, we do not know whether mere energy predictions will be useful for decision-making. Besides making quick probabilistic energy predictions, the energy prediction results need to be processed using statistical methods to provide useful information. There is no method to provide the comprehensive information for decision-making at the early stages, limiting the use of the developed methods just to making energy predictions than design support.

Since operational energy represents a significant portion of the building lifecycle energy [58], the research focuses on operational energy. It further chooses office buildings as a test case, as non-residential buildings have a higher energy demand than residential buildings. Further, the research used the climate of Munich, Germany, classified as Cfb (warm temperate – fully humid – warm summer) in Köppen-Geiger climate classification, which represents most of western Europe [59].

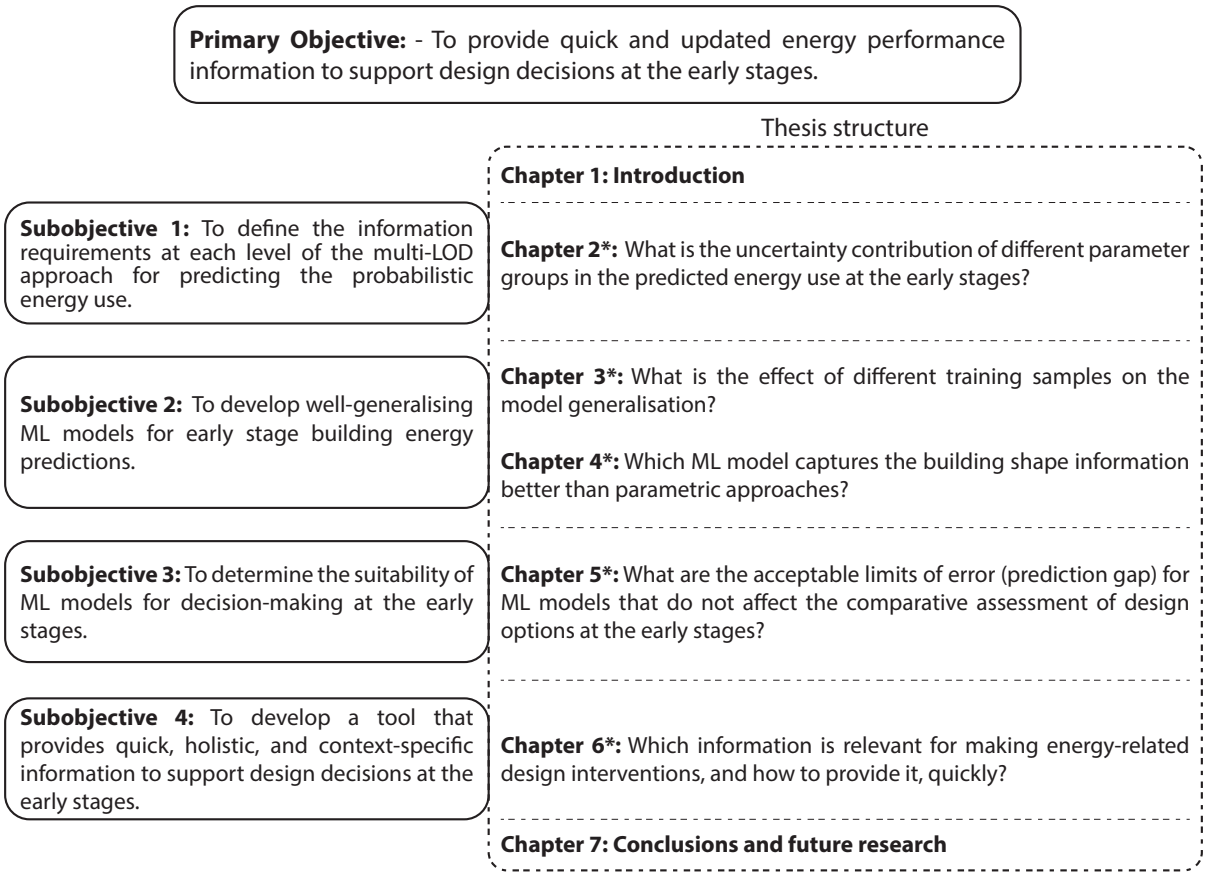
5. Research objectives, questions, and methodology

Designing energy-efficient buildings requires assessing the effects of design decisions from the early stages. Since building design is iterative and evolutionary process, a designer experiments with many possible solutions and assess them on many performance criteria to advance at any design stage. A design change affects the predicted energy use and the effects of other parameters. For example, a change in the window sizes influences effects of the U-value of windows besides the predicted energy demand. Hence, the provided information must be updated according to the new design. In case of evaluating potential designs, it requires continuously updating the energy results specific to the design scenario. For example, if a designer has fixed the U-value of windows, the potential solutions should use a fixed for it. Moreover, the information should be provided in a short time (2-5 minutes) as a designer cannot

wait longer (6-12 hours) for the energy performance results while experimenting with several design possibilities. Hence, the doctoral research has the primary objective as following:

> *"To provide quick and updated energy performance information to support design decisions at the early stages."*

The thesis identified three challenges to using BPS results for decision-making at the early stages – uncertainty in the design information, high computational time, and expensive modelling efforts. Uncertainty in the design information requires simulating several energy models. Since dynamic simulations will take a lot of time for simulating so many models, ML models are developed to quickly obtain BPS results. Further, integrating ML models with BIM tools is required to minimise the energy modelling efforts. The doctoral research is divided into four subobjectives to achieve its primary objective of providing quick and updated energy performance results, as shown in Figure 1.4. The following subsections describe each subobjective, research question, and methodology in detail:



* The doctoral thesis is based on five published articles - four journal articles and one conference article. The published articel is supported by a general introduction at the beginning and an annexure at the end to align its findings with the research objectives.

Figure 1.4 Research objectives, questions, and structure of the thesis

5.1 Subobjective 1: Information requirements for early stage energy prediction

The first subobjective is to develop engineering knowledge to inform designers which parameters should be focussed at each LOD in the multi-LOD approach. It assumes that the parameters are defined with uncertainty at the beginning and a designer focuses on parameters in the order of their ability to influence the uncertainty in energy predictions. For example, if uncertainty in the U-value of walls causes 50% of the uncertainty in energy predictions, it will be advisable to reduce uncertainty in the U-value by developing more details. Achieving this objective requires to estimate the uncertainty contribution of parameters and parameter groups. Parameter groups refer to a logical grouping of parameters, such as, the U-value of wall, floor, and roof are grouped as technical specifications. It is logical to assume that designers will focus on a parameter group at any LOD rather than individual parameters. For example, a designer will finalise all the parameter affecting geometry, simultaneously, at any LOD. The subobjective and question is summarised as follows:

- To define the information requirements at each level of the multi-LOD approach for predicting the probabilistic energy use.

? What is the uncertainty contribution of different parameter groups in the predicted energy use at the early stages?

Previously, sensitivity analysis is used to identify parameters that are required to be defined by accurate distributions to predict probabilistic energy use [28]. It also identified the parameters that can be neglected to improve the sampling efficiency. Thus, it classifies the parameters based on their relevance to make probabilistic energy predictions. Researchers have also used sensitivity analysis to quantify the uncertainty propagation through energy models, i.e., uncertainty contribution of input parameters in the uncertainty of the model outcome [60]. However, it lacks a method that defines the information (parameters) required to make probabilistic energy predictions through multiple stages of design development.

A sensitivity analysis method is used to estimate the uncertainty contribution of uncertain parameters in the uncertainty of energy predictions. A test case of medium-size office building has been used to study the uncertainty caused by different design parameters at the design stages. It calculates the first order and total effects using the variance based sensitivity analysis method [61]. Further, it calculates the uncertainty caused by a group of parameters by summing up their first-order effects. The findings are used to prioritise parameter groups based on their uncertainty contribution in the energy prediction. This part of research concludes with the identification of the parameters to be focussed on at each level of the multi-LOD approach.

5.2 Subobjective 2: Development of ML models for early stage energy prediction

The second subobjective is to develop an ML model for early stage energy predictions. As illustrated earlier, the early stages have uncertain design parameters that requires simulating

several energy models for probabilistic energy predictions. Since dynamic simulations will be time-consuming, ML models are used to make quick energy predictions. The research explores methods to improve the ML model generalisation for the early stages building configurations that are characterised by both parametric and non-parametric (geometrical) variations. The subobjective is summarised as follows:

- To develop well-generalising ML models for early stage building energy predictions.

Developing well-generalising ML models for early stage energy predictions is a very broad research topic. The doctoral research explores two separate concepts to develop well-generalising model by answering two separate research questions:

? What is the effect of different training samples on the model generalisation?

? Which ML model captures the building shape information better than parametric approaches?

The first question focuses on improving the ML model generalisation by training it on large datasets. It is a well-established concept that the generalisation errors reduce with an increase in the number of training samples [62,63]. Since collecting new samples is resource intensive exercise, the research proposes identifying samples that have a higher potential to reduce the generalisation errors. The objective is to develop a resource-efficient data collection approach. The research systematically investigates two data collection approaches – increment and enrichment, to collect new training samples. By comparing the data collection approaches, the study identifies training samples with a higher potential to improve generalisation than others. The training samples collected by increment and enrichment approaches are analysed using a data analysis technique of dimensionality reduction. The research develops a method to quantify the dispersion of training samples based on their shapes. While it is easy to assess the diversity of samples based on parametric characteristic such as U-values, it is challenging to assess diversity based on a non-parametric characteristic such as building shape.

By answering the second question, an improved ML model is developed to capture the shape characteristics. Previously, researchers have developed ML models that use only numerical inputs to predict the energy use. In these models, the shape characteristics are captured by parameters such as shape factor and relative compactness [46,64]. However, it is difficult to capture the effect of building shape on its energy performance using these simple parameters. Hence, the research adapted a convolution neural network (CNN) model structure that captures the shape information from an image and compares it against the existing ML models that uses only numerical inputs. An image that represents the building footprint is used with other parameters as input to the ML model. The CNN model structure processes the shape information from an image that will allow capturing its effect on the energy use predictions better than the parametric approaches.

5.3 Subobjective 3: Effect of substituting simulations by ML models on decision-making

The third subobjective is to investigate the effect of substituting dynamic simulations by ML models on decision-making. ML models represent a deliberate trade-off between accuracy and computational time. Assuming that early stage BPS results are used for the comparative assessment of design options, the research investigates the effect of loss of accuracy on decision-making i.e., comparing design options. It assumes the prediction gap between the ML prediction and dynamic simulations is 'small' if it does not affect the decision-making under uncertain conditions of the early stages. It is imperative to find acceptable limits of error that do not affect decision-making before using the ML model in a design support tool. Hence, the subobjective and associated research question is summarised as follows:

- To determine the suitability of ML models for decision-making at the early stages.

? What are the acceptable limits of error (prediction gap) for ML models that do not affect the comparative assessment of design options at the early stages?

The doctoral research investigates different approaches to perform energy predictions and compare design options under uncertainty. A reference method is developed that uses dynamic simulations to predict energy use, a probabilistic approach to address uncertainty, and a detailed zoning (core-and-perimeter-zone) to create zones. The reference method provides an accurate comparison of design options but at a high computational cost. While alternative approaches are computationally efficient but errors in the energy predictions may cause inaccurate comparison results. Three alternative approaches are tested to reduce the computational time. An alternative deterministic approach is used to address uncertainty, simplified approach to create zones, and an ML model to make predictions. The approaches are compared based on modelling efforts, time requirement, and accuracy. These findings will conclude whether the ML models are reliable for energy predictions and decision-making at the early stages.

5.4 Subobjective 4: Development of ML and BIM based tool to support design decisions

The fourth subobjective is to develop a tool that provides information to support energy related design decisions. The information can range from probabilistic energy prediction of design options to sensitivity values for design parameters to comparing several design options. In a continuously changing and uncertain design conditions of the early stages, we need a tool that quickly evaluates several probable solutions and provides a context-specific energy information. For example, if a designer has changed window-to-wall ratios, it expected to directly influence the effect of the U-value of windows and walls, and the g-value of windows on the predicted energy use. The tool should evaluate probable solutions for the modified context of new window-to-wall ratios. Further, it should provide information rather than just predicting the energy use. The tool should also be quick to fit in the context of the early stages. Hence, the subobjective and research question can be summarised as follows:

- To develop a tool that provides quick, holistic, and context-specific information to support design decisions at the early stages.

? Which information is relevant for making energy-related design interventions, and how to provide it, quickly?

The doctoral research develops a tool to provide relevant information for design support facilitated by ML and BIM. ML models instead of dynamic simulations predict the energy demand for several probable solutions in a short time. The BIM integration allows updating the energy models with the minimum modelling efforts by reusing the design information. The research implements the ML model into a cloud based service that uses geometrical information from the BIM model. It makes quick energy predictions for several possible combinations of design parameters. The tool further processes the energy prediction results to provide information for design space explorations, analyse and compare design options, sensitivity analysis, and tracks progress. A few researchers and architects are invited to use the tool for designing an energy-efficient building. Their responses have been recorded to understand the benefits and limitations of the tool.

6. Structure of the thesis

The doctoral thesis is organised into seven chapters, as shown in Figure 1.4. Chapter 1 provides introduction to the thesis. Each chapter, from Chapter 2 to Chapter 6, deal with a specific research question, described in section 5. The last chapter, Chapter 7 draws conclusions based on the research objectives and questions. It also describes the findings with limitations and identifies the future research avenues. Chapter 2 to Chapter 6 have been already published as a journal or conference article. Some corrections are made to the published version as mentioned on the chapters' title page. The chapters have a general introduction and annexure to improve the readability of the published article and incorporate comments of the doctoral committee.

The following paragraphs describe the content of each chapter:

Chapter 1: Introduction and background

The chapter discusses the motivation behind this doctoral research, identifies challenges to early stage energy predictions and developing a design support tool, knowledge gaps, and scope of the research. It describes the primary research objectives, subobjectives and research questions, and the thesis structure.

Chapter 2: Information requirements for multi-LOD BIM

Focussing on the first subobjective, the chapter calculates sensitivity indices for design parameters at the early stages. The sensitivity values are used to define the information requirements at each level of the multi-LOD approach from energy perspective. These findings are helpful to reduce uncertainty in the energy predictions by detailing the design information in the order of their influence.

Chapter 3: Data increment and enrichment for training ML models
The chapter addresses the subobjective of developing a well-generalising ML model. It answers the question of which training samples are useful to improve the model generalisation. It identifies the training samples with a higher ability to reduce the generalisation errors by comparing the two data collection approaches. The distribution of training samples is analysed based on the building shape. The corresponding change in the model generalisation is studied to identify a better data collection approach.

Chapter 4: CNN for early stage ML based energy prediction model
The chapter addresses the subobjective of developing ML models by investigating which ML model is appropriate to capture the interaction between building shape and its energy performance. The findings have been extended to develop ML models for two other locations – Brussels and Berlin.

Chapter 5: Quick energy prediction for comparing design options
The chapter investigates the suitability of the ML model for comparative assessment of design options at the early stages. Using a test case, the chapter discusses whether the prediction gap caused by the ML model is 'small' enough to compare design options under uncertainty.

Chapter 6: Context-specific design support using ML and BIM
The chapter develops the tool to support design decisions at the early stages. It uses the ML model trained in Chapter 4 to provide various information that are useful to make energy-related design decisions. By demonstrating the tool's functionality on a test case and collecting the users' feedback, the chapter discusses the usefulness and limitations of the tool and avenues for future development.

Chapter 7: Conclusions and future research
The chapter summarises the findings in the context of the stated doctoral research objectives. It further discusses the limitations of developed methods that open discussion for further research. While addressing the limitations, potential future research avenues have been identified to pave the way for developing design support tools.

2

Information requirements for multi-LOD BIM

Chapter 2.
Information requirements for multi-LOD BIM *

General introduction

The chapter aims to achieve the first subobjective of developing engineering knowledge to inform designers which parameters should be focussed at each level of the multi-level-of-development (LOD) approach. Designers can reduce the maximum part of uncertainty by prioritising the parameters having a significant effect on energy predictions. The chapter answers the following question using a sensitivity analysis method:

? What is the uncertainty contribution of different parameter groups in the predicted energy use at the early stages?

By conducting a sensitivity analysis study on energy models of medium-size office buildings, the chapter quantifies the uncertainty caused by various design parameters. It assumes different

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* The chapter is originally published as the following article in a peer-reviewed journal.

M.M. Singh, P. Geyer, Information requirements for multi-level-of-development BIM using sensitivity analysis for energy performance, Adv. Eng. Informatics. 43 (2020) 101026. https://doi.org/10.1016/j.aei.2019.101026

The general introduction and annexure were not part of the published article and have been added to align its findings with the doctoral research objectives. The chapter's content has been revised, significantly, to address comments of the PhD committee.

The doctoral researcher has conceptualised, developed methodology and software tools, conducted formal analysis and investigation, visualised the results, and written original draft and revisions. The last author has helped in conceptualisation and writing the article.

geometric variations and acceptable ranges for design parameters to emulate the early stages. The design parameters are divided into five groups – geometrical, technical specifications, window parameters, building operation, and equipment efficiencies. It is more logical to assume that designers will focus on a parameter group instead of individual parameters at any LOD. For example, designers will focus on the U-values of walls, floors, and roofs rather than focussing on these at different LODs. The multi-LOD concept requires all the parameters to be defined with uncertainty at the beginning of the design process. Hence, it is required to make suitable assumptions in the design parameters to conduct sensitivity analysis. After making a few initial trials, the chapter assumes ±10% uncertainty in the geometrical parameters and ±25% uncertainty in technical specifications, window parameters, building operation, and equipment efficiencies. The geometrical parameters are limited to ±10% uncertainty as a higher value will affect the building utility (floor area will increase or decrease too much).

Sensitivity analysis is performed using the variance based method that uses an analysis of variance approach to estimate two sensitivity indices – the first-order effect and total effects [61]. Assuming that variance represents the uncertainty in the model outcome (predicted energy use), the first-order effect of a parameter signifies part of the uncertainty that can be removed by fixing its value [32,65]. Fixing the value of a parameter refers to developing the design details. Such as U-value for walls can be fixed by developing the details of construction layers and their thicknesses. The chapter estimates the uncertainty caused by a parameter group by summing up the first-order effects of the parameters. The findings are used to define which information is required at each LOD to predict the energy use and make it more precise as the design progresses. Designers can use this information to prioritise design decisions from the energy perspective.

Information requirements for multi-level-of-development BIM using sensitivity analysis for energy performance

Abstract: The concept of multi-level-of-development (multi-LOD) modelling represents a flexible approach of information management and compilation in building information modelling on a set of consistent levels. From energy perspective at early stages, the refinement of design parameters by adding information allows a more precise prediction of building performance. The need of energy-efficient buildings requires designers to prioritise energy-relevant decisions by focussing on parameters in the order of their ability to reduce uncertainty in the predicted energy use. However, there is no method for assigning and prioritising information at a particular LOD. Therefore, the article performs sensitivity analysis to estimate the uncertainty caused by design parameters in energy predictions. We studied parametric energy models of several building shapes representing architectural design variations at the early stages. The variance based method is used to calculate the uncertainty contribution of design parameters. The sensitivity values are used to rank the design parameters in the order of their influence on uncertainty in energy predictions and determine the information required at each LOD. Based on the uncertainty contribution by parameter groups, three levels of uncertainties are identified. These findings form the basis to define information requirements at each LOD of the multi-LOD approach. The first level includes geometrical parameters, the second level includes technical specification, and the third level includes window parameters. The findings provide an engineering basis to define information requirements in a multi-LOD approach and prioritise performance relevant decisions at the early stages.

Keywords: multi-LOD modelling; variance based sensitivity analysis; uncertainty analysis; architectural design; building energy model.

1. Introduction

The process of building design is described as an increase of information in the digital model. However, designing takes place in the process of switching between levels. This process is often described as scaling [15,16]. The multi-level of development (multi-LOD) concept is introduced to overcome several challenges of the traditional design process that enables an informed decision-making integrating performance prediction [17,66]. It is based on the concept that design parameters are defined with uncertainty, initially, as shown in Figure 2.1. The figure shows five parameter groups – geometrical parameters, technical specifications, window parameters, building operation, and equipment efficiencies. These parameter groups represent a logical group such as parameters, U-values of walls, floors, and roofs, and air permeability are grouped under technical specifications. Moreover, it is logical to assume that designers will focus on a parameter group at any LOD than individual parameters. The figure

assumes that geometrical parameters cause the maximum uncertainty, followed by technical specification, and window parameters. Hence, a designer focusses on geometrical parameters at LOD 1, technical specifications at LOD 2, and window parameters at LOD 3. By following this understanding, the maximum uncertainty in the energy predictions is removed at LOD1 by finding precise values for geometrical parameters. Building operation and efficiency parameters such as operating hours and boiler efficiency are considered to remain uncertain after the design.

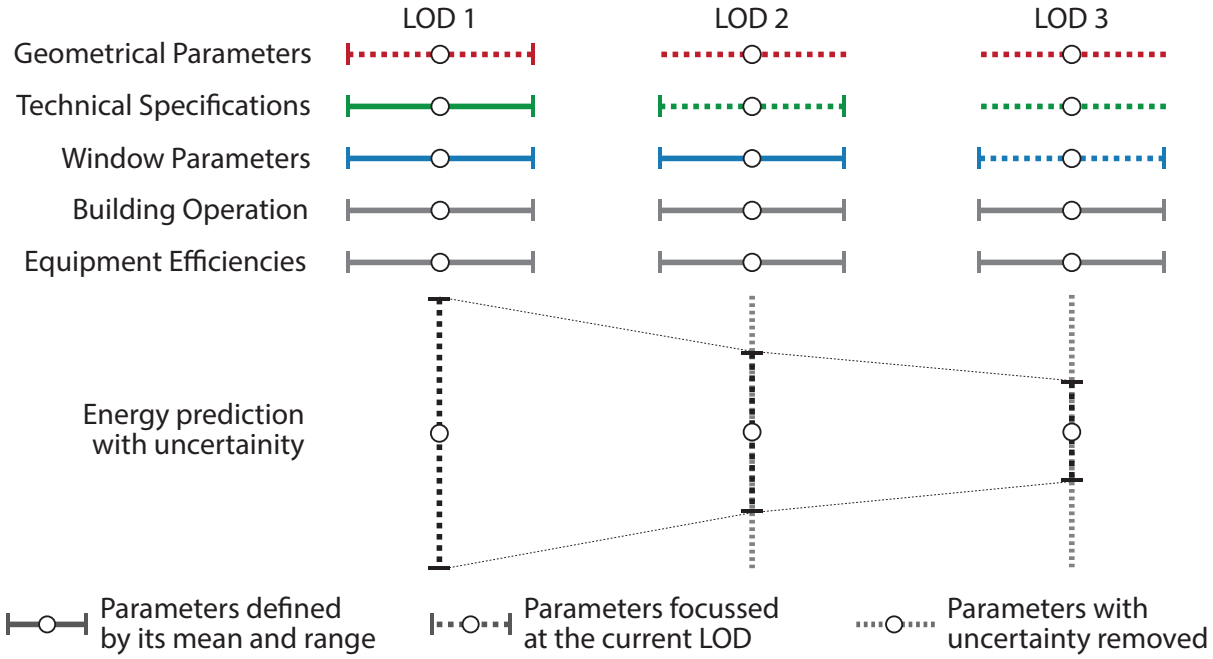

Figure 2.1 Parametric uncertainty in a multi-LOD approach

The multi-LOD approach represents the evolutionary and iterative nature of the design process, more appropriately [10]. However, it lacks engineering basis to define information requirements at any LOD for prioritising energy relevant design decisions. For the prioritisation, we need sensitivity analysis to ascertain which design parameters should be focussed at each LOD. Sensitivity analysis methods allow quantifying the influence of design parameters on the predicted energy performance, thus, its ability to reduce the uncertainty in it.

Energy-efficient solutions have been one of the prime focuses of research in building design, given that approximately one-third of global energy is required to operate the buildings [67,68]. To reliably reduce the energy consumption of buildings, it will be imperative for designers to focus on the parameters with a strong influence at the early stages. The sensitivity analysis of the energy model is performed to prioritise the design parameters in the order of their effect on the energy use. According to the multi-LOD approach, there is a potential to streamline the design process with energy prediction by the appropriate use of building information modelling (BIM) data structures [17]. The approach will be supported by focussing on suitable design

parameters at each LOD, prioritising the energy related design decisions. The focus is on the design phase of the building life cycle when the information regarding shape, size, and technical specification is developed. The article aims to understand which design parameters to be focused on at any level of the multi-LOD approach. The objectives of the article are:

1. To determine the sensitivity of design parameters in the energy model of different building shapes.
2. To identify uncertainty levels for information required at each level of the multi-LOD BIM approach.

The article is structured in sections – literature review, research methodology, results, discussion, and conclusions. The literature review section documents previous research works on the sensitivity analysis of energy models, selection of sensitivity analysis method, and identifies research gaps. The research methodology section explains test case, alternative shapes, and the calculation of sensitivity indices and uncertainty. The results section documents sensitivity indices, ranking of parameters, uncertainty contribution, and information requirement for multi-LOD approach. The discussion section describes the limitations of the methodology and results. The conclusion section describes the applicability of results in a broader context of building design.

2. Literature review

Sensitivity analysis has been a common method to study the effect of design parameters on energy predictions as many parameters are inherently uncertain at the early stages [69]. The global sensitivity analysis methods are used to rank the parameters in the order of their effects and quantify the uncertainty in the output variable [24,70–72]. These studies are focussed on design support [73], assessing the robustness of energy models [74], and variation in the output variable [75,76]. However, it lacks a study linking the information required at different LODs with the uncertainty in the energy predictions. Such study is required to prioritise energy related design decisions and identify information required to make more precise energy predictions as the design progresses.

Previous studies have implemented various global sensitivity analysis methods, such as the Morris method, regression, and variance based methods to study the effect and behaviour of design parameters in energy models [32,77,78]. Each method offers a few advantages over others based on the scenario under consideration. The Morris method helps rank parameters and delivers information on the behaviour of parameters. The regression based methods are suitable for linear models with less parameter interaction [79,80]. The variance based method calculates sensitivity indices without determining the model structure, making it more robust for complex models [81]. In general, a building energy model is expected to contain higher-order effects and parameter interactions. Thus, the variance based method is more suitable for the early stage building energy models. Furthermore, the sensitivity indices using the variance

based method calculate the amount of uncertainty that can be removed by fixing the design parameter [32].

The sensitivity analysis studies of building energy models differ from each other in terms of test cases and parameters. Most of these studies examine the energy models of fixed architectural shape and size [32,82–84] or rectangular buildings of variable dimensions [77,85]. However, fixing the shape is not representative of the early stages when designers are interested in developing building shape. Designers develop the building shape based on multiple criteria such as aesthetics and its function. However, the building shape influences the energy predictions and the behaviour of other parameters. Hence it is imperative to study the energy models of several building shapes to generalise the results for the early stages. The article is aimed to bridge the following research gaps: -

1. Previous research works study the effect of design parameters for the energy models of fixed shape or rectangular shape of flexible dimensions. These studies do not capture the effect of different shapes and its interaction with other parameters. Since the building shape is also flexible, these findings cannot be generalised for the early stages.
2. Uncertainty analysis has been used to estimate the uncertainty caused by individual parameters, while the uncertainty contributions by parameter groups are more relevant to identify the information required at each LOD. These findings are required to prioritise energy related decisions at the early stages.

3. Research Methodology

The methodology section is divided in five subsections. Subsection 3.1 describes the test case with alternative building shapes. Subsection 3.2 provides details of parameters studied and their selection. Subsections 3.3 describes the sensitivity analysis method and 3.4 details out the procedure for calculating sensitivity indices and uncertainty contribution. Subsection 3.5 determines the adequate number of samples for the sensitivity analysis study.

3.1 Test case

The sensitivity analysis study is performed on a test case building near Munich, Germany – Tausendpfund. The selected building represents an average-sized office building with a total floor area of 1200 ($14.8 \times 27.0 \times 3$) m^2, equally distributed over three floors and floor-to-floor height of 3.25 m. The climate of Munich is classified as Cfb (warm temperate – fully humid – warm summer) in Köppen-Geiger climate classification, which represents most part of western Europe [59]. The building's heating and cooling energy demand has been measured for year 2017 and 2018. Based on the information available about the building, we have created an EnergyPlus [33] model and calibrated its parameters. Appendix A provides the relevant details of the building energy model, calculated, assumed, and calibrated design parameters. The calibrated EnergyPlus model used one-zone-per-floor approach to create one thermal zone on each floor [86]. The approach is widely used in the absence of information about thermal zones

and create simplified energy models for the early stage energy predictions [77,85]. The model outcome or the predicted energy use accounts for the energy required to provide heating, cooling, and lighting. The effect of available daylight to reduce the requirement of artificial lighting is also considered. More details of the energy model are documented in Appendix A.

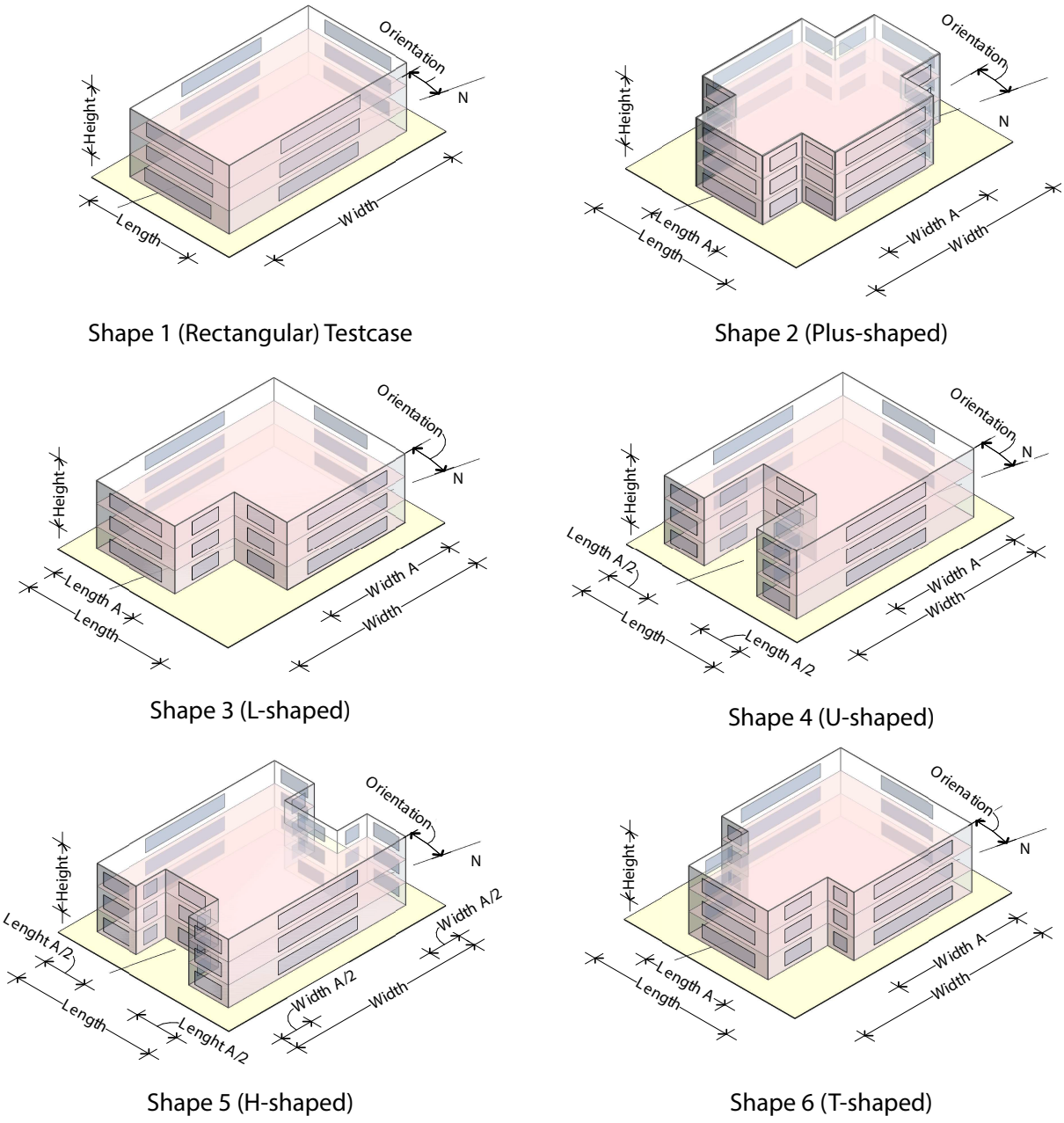

Figure 2.2 Architectural design variations studied in the research

We represent shape variations (non-parameterised) of the early stages by the test case and alternative building shapes, as shown in Figure 2.2. Alternative shapes support the objective of

having a representative range of design variants to correctly assess parameter sensitivities and their interaction with the shapes. Shapes 1, 2, 3, 4, 5, and 6 represent rectangular, plus-shape, L-shape, U-shape, H-shape, and T-shape floor plans, respectively. These geometrical configurations are commonly used in small and medium-size office building designs [87,88]. All shapes are configured to provide a similar floor area as the rectangular shape. It means that Length and Width of Shape 2 to 6 are slightly increased to compensate for the area removed from the rectangular shape. Four geometrical parameters, Length, Width, Height, rLength (Length A = rLength × Length), and rWidth (Width A = rWidth × Width), represent further variations in the size.

3.2 Selection of parameters' ranges

We studied the influence of parameters, listed in Table 2.1, on reducing the uncertainty in the predicted energy demand. The parameters are grouped based on their nature; for instance, length, width, rLength, rWidth, height, and orientation are grouped as geometrical parameters. In total, the parameter groups are identified as geometrical parameters, technical specification, window parameters, building operation, and equipment efficiencies. The ranges of design parameters is selected based on German EnEV standards [22], Passive House institute [25], and information available about the building [89]. After few trials, we selected arbitrary ranges of ±10% for geometrical parameters and ±25% for the remaining parameter groups. The idea is to assign a uniform variation to all the design parameters and assess their ability to influence the uncertainty of energy predictions. However, assuming the variation of more than ±10% in geometrical parameters is not viable, as it will change the floor area by a big margin, rendering the parameters' sensitivities unreliable. Further, the following paragraphs describe the strategy used to determine an appropriate range for each parameter:

Geometrical parameters: The two basic geometrical parameters, Length and Width are constrained in the range of mean value ±10%, where the mean value is the same as the dimensions of the testcase building. These two parameters directly influence the floor area. A higher variation in these two parameters will reduce or increase the floor area, too much, and the results will be unreliable. A suitable increase in Length and Width is considered for Shape 2 to Shape 6 as it will require higher dimensions to achieve the same floor area as Shape 1. The total height of the building is 9.75 m and with ±10% variation, the range has been fixed between 8.78 and 10.73 m. The building has orientation of 20 degrees from North and it is allowed to rotate the building on site by a margin of ±5 degree. Hence, its range is fixed between 15-25 degrees. The two additional parameters rLength and rWidth are assigned with the range of 0.8 ±10% or 0.72-0.88. These are the factors to Length and Width and do not affect the floor area, directly.

Technical specification: The group has U-values of solid components and air permeability. Since these parameters will be finalized at a later stage than geometrical parameters, a higher variation of ±25% is considered for these parameters. The German standard describes that the

reference building should have the U-value 0.28, 0.25, and 0.35 W/m^{2}K for walls, roofs, and floors, respectively. Considering these values as the upper limit and applying ±25% variation, provides the range of U-value (wall) to be 0.17-0.28, U-value (roof) to be 0.15-0.25, and U-value (ground floor) to be 0.21-0.35 W/m^{2}K. We considered Type-II construction and based on the standard; it should have the air permeability of less than 6 m^3/m^{2}h. With the same variation of ±25%, the range will be 3.6-6.0 m^3/m^{2}h.

Table 2.1 Details of design parameters

Group	Parameter	Unit	Min	Max
Geometrical Parameters	Length	metres	13.2	16.2
	Width		24.3	29.7
	Height		8.78	10.73
	rLength	-	0.72	0.88
	rWidth		0.72	0.88
	Orientation	degrees	15	25
Technical Specifications	U-value (wall)	W/m^{2}K	0.17	0.28
	U-value (floor)		0.21	0.35
	U-value (roof)		0.15	0.25
	Permeability	m^3/m^{2}h	3.6	6.0
Window Parameters	U-value (window)	W/m^{2}K	0.65	1.09
	g-value	-	0.26	0.44
	WWR (N)		0.23	0.38
	WWR (W)		0.23	0.38
	WWR (S)		0.23	0.38
	WWR (E)		0.23	0.38
Building Operation	L/EHG	W/m^2	13.5	22.5
	Operating Hours	hours	8.25	13.75
Equipment Efficiencies	Boiler Efficiency	-	0.8	0.98
	Heating COP		2.1	3.5
	Cooling COP		2.7	4.5

Window parameters: A typical triple-glazed window has a U-value of 0.85 W/m^{2}K and g-value of 0.35, including the frame. By applying the variation of ± 25%, the range for U-value will be 0.65-1.09 W/m^{2}K and for g-value will be 0.26-0.44. The testcase building has the window-to-wall ratio (WWR) of 0.3 in each direction. With the same variation of ±25%, the range will be 0.23-0.38.

Building operation: The group of parameters is related to the building operation. Since there are no prescribed values for these parameters, we have taken mean value as in the testcase building and applied ±25% variation. The testcase building operates for 11 hours a day and the range for operating hours has been taken 9-13 hours. The light and equipment heat gain in 18 W/m^2; hence, the range of 14-22 W/m^2 is taken.

Equipment efficiencies: The test case building has a heat pump that provides heating and cooling and a boiler that provides additional heating. The heat pump has rated coefficient of performances of 2.8 for heating and 3.6 for cooling. We applied ±25% criterion to define the ranges. The boiler has the rated efficiency of 0.95; however, the maximum possible limit is 0.98 for an electric boiler. Hence, we cannot apply the same variation of ±25%. We selected the range of 0.8-0.98 that represents the range of mean value ±10%.

3.3 Variance based sensitivity analysis

We implemented the variance based sensitivity analysis method to study the effect of design parameters on energy prediction. Two sensitivity indices are calculated using the variance based method, i.e., the first order effect S and total effects S^T. The first order effect estimates the fraction of variance, i.e., uncertainty in model outcome which can be removed if a value is assigned to it [32]. Thus, it is suitable to identify the parameters with significant influence on the model outcome [90,91]. The higher value of S shows that the parameter has a bigger effect on the model outcome and will have a better rank than others. The value of S^T represents the total effect of a design parameter, including interactions and higher-order effects. S and S^T are the comparative measure of sensitivities and represent the effect of a parameter with respect to the overall effect of all the parameters [92]. The sensitivity indices, S and S^T, are calculated using the method described in Saltelli et al. 2010 [81].

3.4 Calculation of sensitivity indices and uncertainty contribution

The calculation of sensitivity indices starts by setting up a sample matrix, followed by calculating energy demand (model outcome) and variance analysis. Since the building shape is not parameterised, the sensitivity indices are calculated for different shapes, separately. The sample matrix **X**, of size (n × p) representing n configurations of p parameters, is set up using SALib python library [93], as shown in Eq. (1). Six sample matrices have been setup corresponding to each shape.

$$X = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & \cdots & x_{1,p} \\ x_{2,1} & x_{2,2} & \cdots & \cdots & x_{2,p} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ x_{n,1} & x_{n,2} & \cdots & \cdots & x_{n,p} \end{bmatrix} \; and \; Y(X) = \begin{bmatrix} y_1 \\ y_2 \\ \cdots \\ \cdots \\ y_n \end{bmatrix} \qquad \ldots Eq.\ (1)$$

A program is developed that generates EnergyPlus input data files corresponding to each configuration. The energy use of each configuration is simulated using EnergyPlus [33]. We

used high performance computing cluster of ten nodes equivalent to 360 cores at a clock speed of 2.3 GHz. It allows running EnergyPlus simulations in parallel, reducing the time required to generate data. The model output corresponding to each design configuration is mapped to get the model output vector Y(X). The variance of Vector Y(X) is analysed to calculate sensitivity indices, S and S^T for each parameter. The uncertainty attributed to a group of parameters is calculated by summing up their absolute first order effects. The approach ignores the contribution towards uncertainty caused by interaction and higher-order effects. If the higher-order effects and interactions are not significant, it will provide a reliable measure of uncertainty which can be removed by assigning a value to the parameter. The sum of interactions and higher-order effects is calculated by subtracting the first order effect from the total effects. To analyse the information required at various levels of the multi-LOD approach, the three levels of uncertainty are set up based on the observations. Designers should focus on parameter groups that exceed the LOD's threshold.

3.5 Number of samples

The required number of samples is tested by calculating the mean absolute error (MAE), as described in Saltelli et al. 2010 [81]. The validity of the method depends on MAE, which decreases with an increasing number of samples. MAE is defined by Eq. (2), where j denotes the number of randomisations used to calculate the error. Each randomisation uses a subset of samples from the dataset of specified number of samples. $S_i^T(j)$ denotes the total effects of ith parameter in j^{th} randomisation and S_i^T is the average of total effects for i^{th} parameter over all randomisations.

$$MAE = \frac{1}{50}\sum_{j=1}^{50}\sum_{i=1}^{p}\left|S_i^T(j) - S_i^T\right| \qquad \text{... Eq. (2)}$$

If the number of samples is N and the number of parameters is p, then it requires n=N×(p+2) configurations to generate the data for the variance based sensitivity analysis. The tests are conducted starting with a small number of samples and increasing the samples, gradually. The preliminary test is conducted with 50, 100, 200, 400, and 600 samples for Shape1. The values of MAE for the number of samples are plotted in Figure 2.3. The number of simulations represents the computational efforts as the simulations is the most time-consuming activity in the process. The computational efforts increase linearly with the number of samples. By increasing the samples from 50 to 100 reduces the error by 38%, to 200 reduces the error by 61%, to 400 reduces the error by 74%, and to 600 reduces the error by 80%. The decrease in the error is much smaller for the samples more than 200. So, for further analysis, the data has been collected with 200 samples for each shape. The number of parameters is 19 for Shape 1 and 21 for Shape 2 to 6. Hence, the number of configurations is 200×(19+2) = 4200 for Shape 1 and 200×(21+2) = 4600 for Shape 2 to 6.

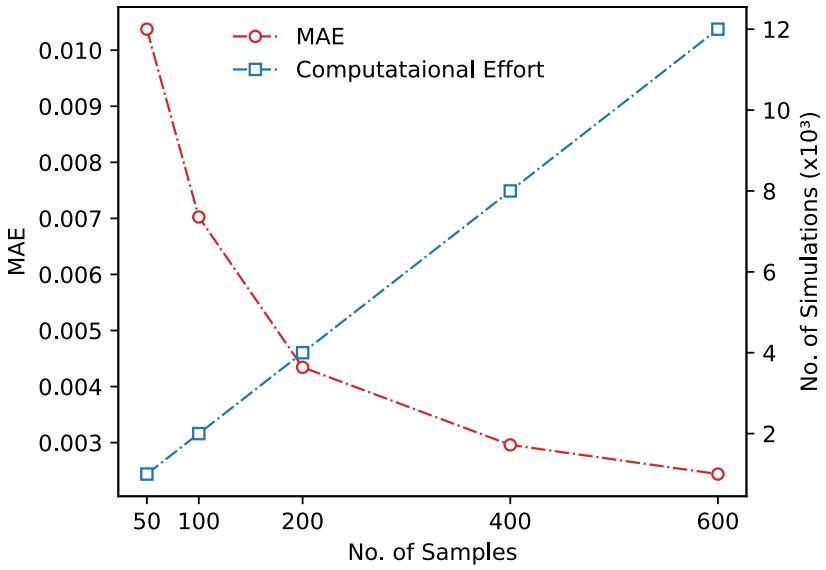

Figure 2.3 Number of samples for variance based methods

4. Results

The parameters' sensitivities are calculated for each shape and the results are documented in this section. Section 4.1 presents the values of sensitivity indices and the ranking of parameters. Section 4.2 documents the calculation of uncertainty contribution, and section 4.3 details the information required for each level of multi-LOD.

4.1 The first order and total effect

The sensitivity indices are calculated using 200 samples for each shape using the variance based method. Figure 2.4 shows the values of S and S^T as a bar graph. The first observation is whether the parameters' sensitivities change across different shapes. There are little variations in parameters' sensitivities across shapes. The first order effect and total effects for length, width, height, and permeability are slightly different for Shape1 than other shapes. The first order effect of U-values of roof and floor, WWRs, L/EHG, and COPs are much lower compared to other parameters. The first order effects of Permeability, Height, Width, U-value (window), Length, Operating Hours, Boiler Efficiency, g-value, and U-value (wall) are close to 0.2, 0.19, 0.15, 0.08, 0.08, 0.07, 0.06, 0.05, and 0.04, respectively, making these most influential parameters. All the other parameters have the first order effect of less than 0.01.

The parameters are ranked based on the first order effect for each shape, and the results are plotted as a trendline in Figure 2.5. The figure analyses whether the parameters' ranking change across different shapes. The figure also has the parameters' ranking for All Shapes, based on the mean value of the first order effects calculated over all the shapes. There is only little change in the ranking of most influential parameters, Permeability, Height, Width, U-value (window), Length, Operating Hours, Boiler Efficiency, g-value, and U-value (wall). These parameters are ranked in the same order as mentioned for All Shapes. For the remaining parameters, the rank

of parameter changes across shapes. However, their first order effects are lower than 0.01 and small changes in their values lead to abrupt changes in the ranking across shapes. Hence, we can use this information to rank the parameters with a high influence; however, the same is not true about the parameters with a small influence on the energy predictions.

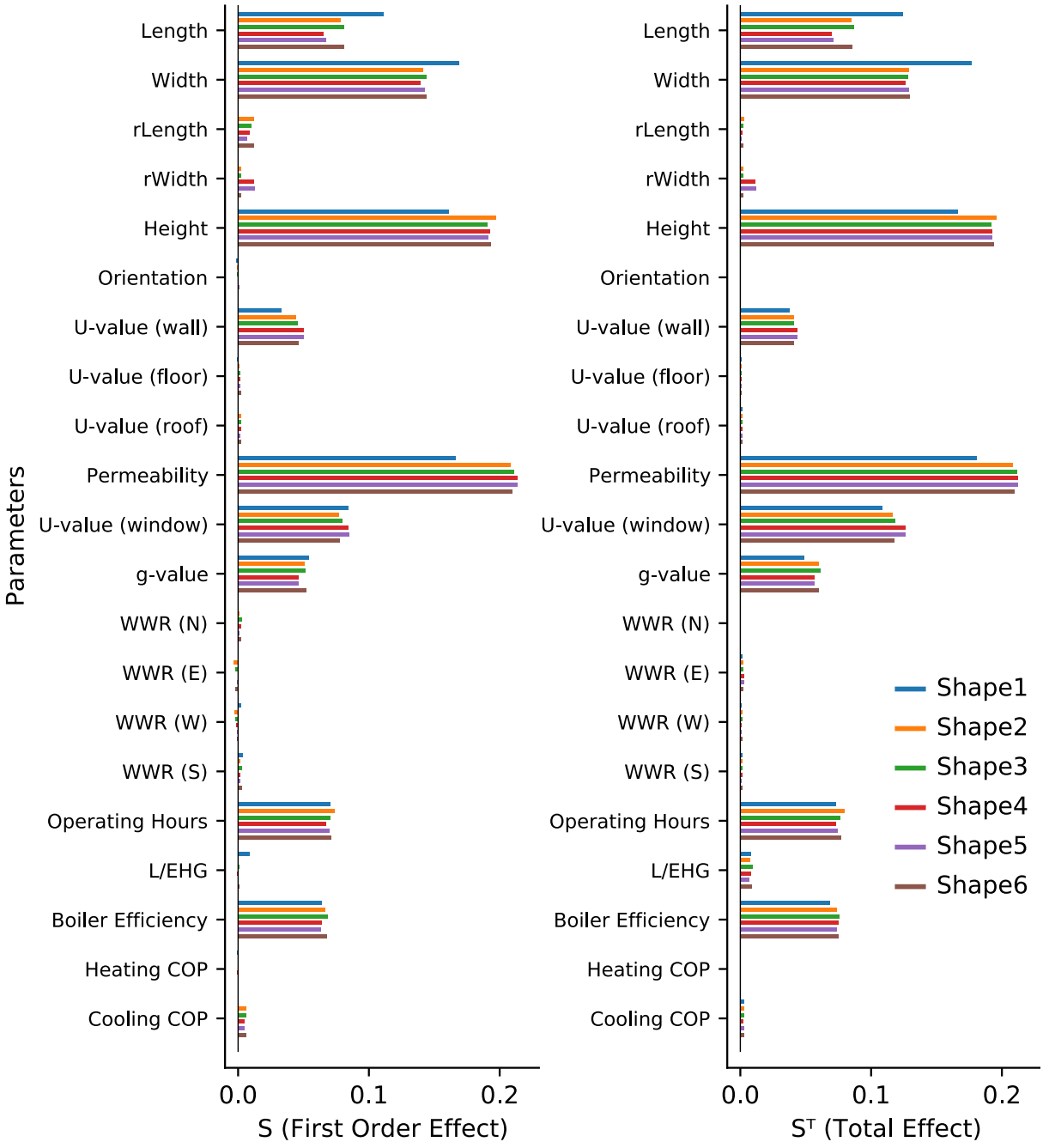

Figure 2.4 The first order and total effect of parameters for different shapes

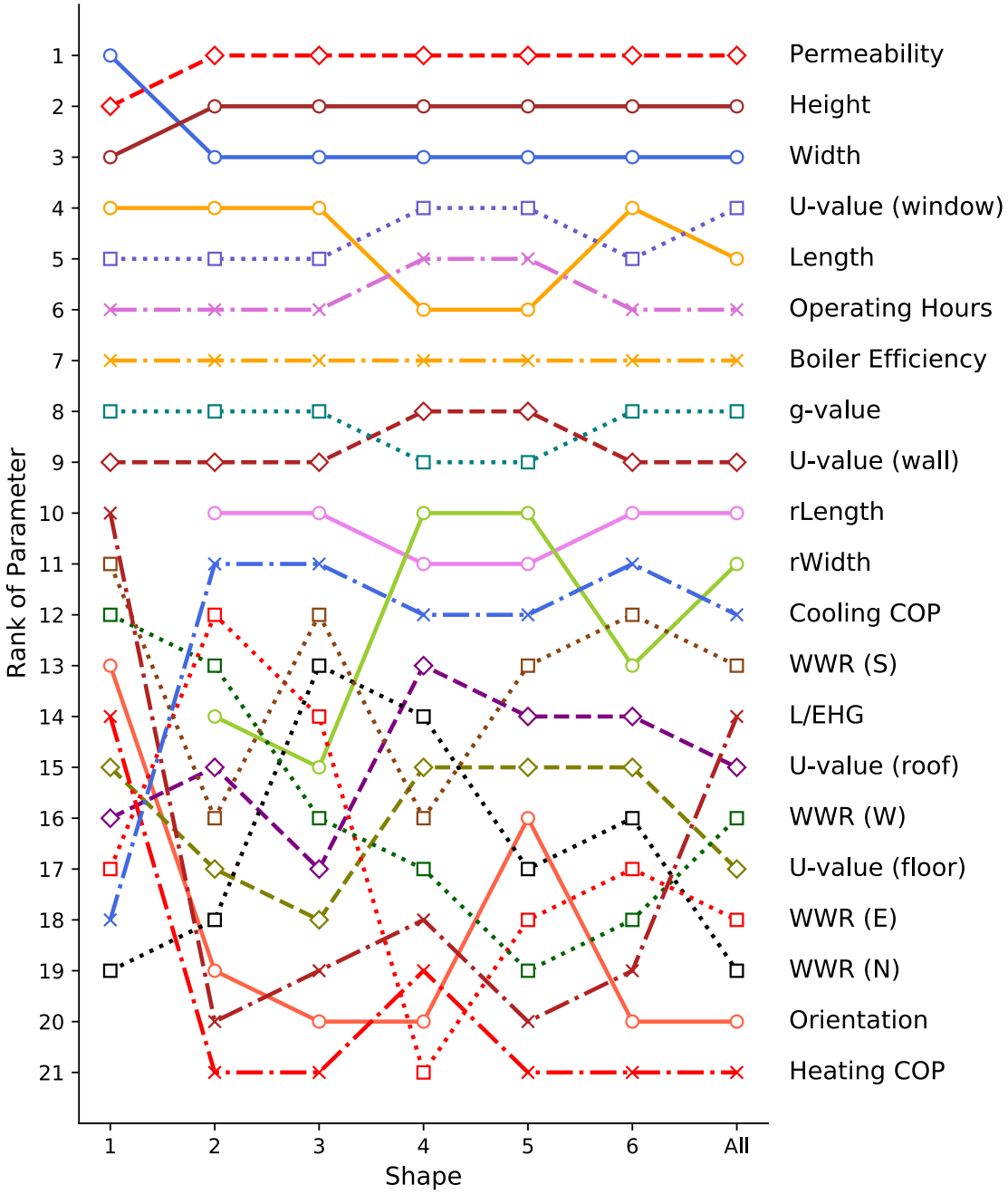

Figure 2.5 Ranking of parameters for each design alternative

4.2 Estimation of uncertainty in energy prediction

The uncertainty in energy prediction attributed to parameters groups is calculated by summing up the absolute value of the first order effect of the parameters. The sum of values of higher-order effects and interactions of all the parameters is close to 0.05, hence, ignored for calculating the uncertainty contribution. Figure 2.6 shows the uncertainty contribution of the parameter group as a bar plot. There seems to be only a little variation in uncertainties across different building geometry. More than 40% of the uncertainty in energy predictions is

represented by geometrical parameters. The technical specifications cause more than 1/5 of the total uncertainty. Window parameters cause more than 10% of the uncertainty, due to high first order effects of U-value (window) and g-value. Operational design and equipment efficiencies has the first order effect of less than 8%, individually.

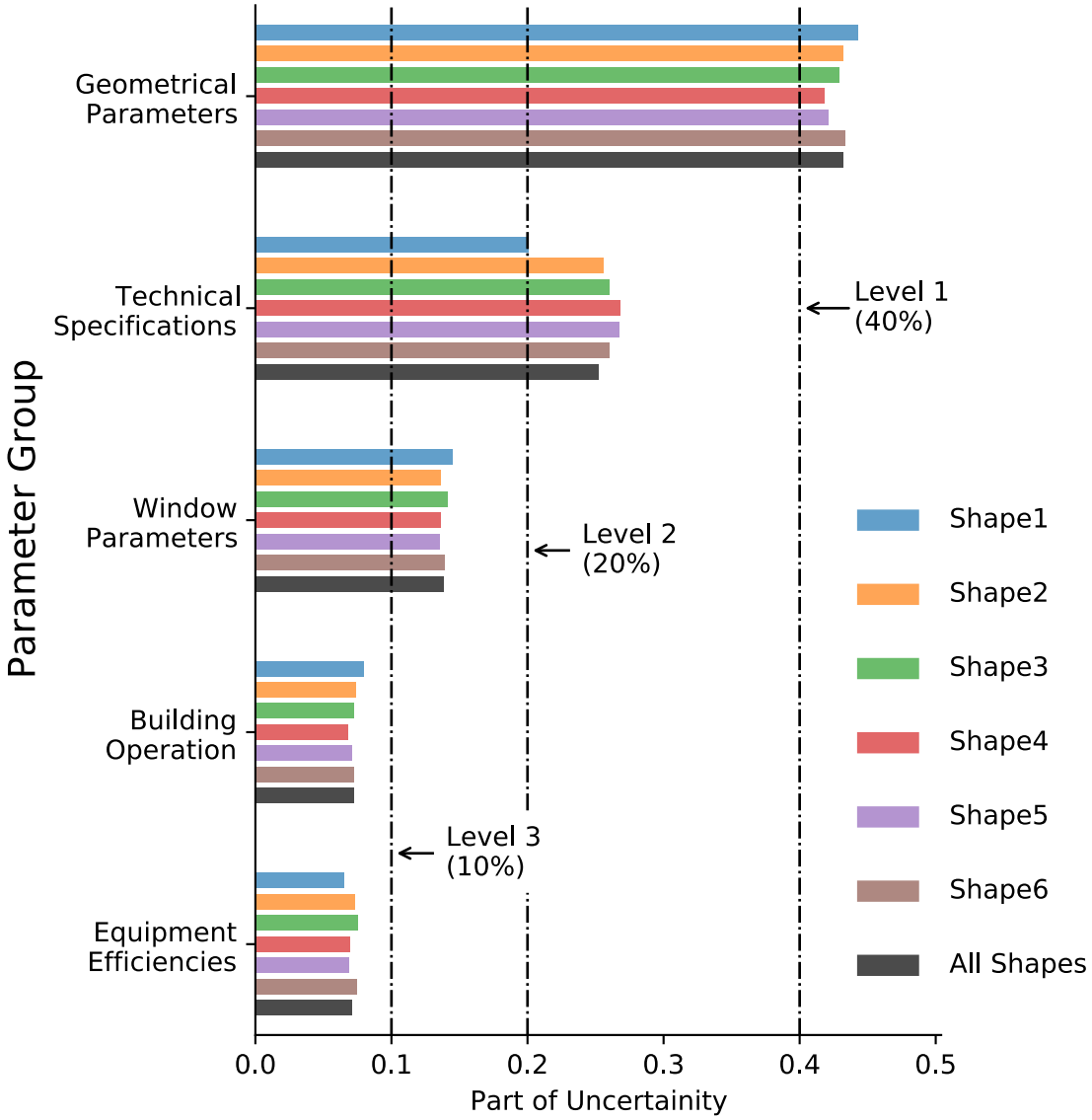

Figure 2.6 Uncertainty attributed to a group of parameters for energy prediction

4.3 Levels of uncertainties and information requirement for multi-LOD approach

After calculating the uncertainty contribution by a group of parameters, the three levels of uncertainties are identified at 40%, 20% and 10%, as shown in Figure 2.6. These levels are used to determine the information required in the multi-LOD approach. The geometrical parameters cause the most part of uncertainty for all shapes. Thus, finding the suitable value for geometrical parameters is of utmost importance and should be prioritised at the first level of the multi-LOD

approach. A designer should focus on technical specifications at the next level, which causes more than 20% of uncertainty. At the third level, decisions on window parameters will reduce uncertainty by more than 10%.

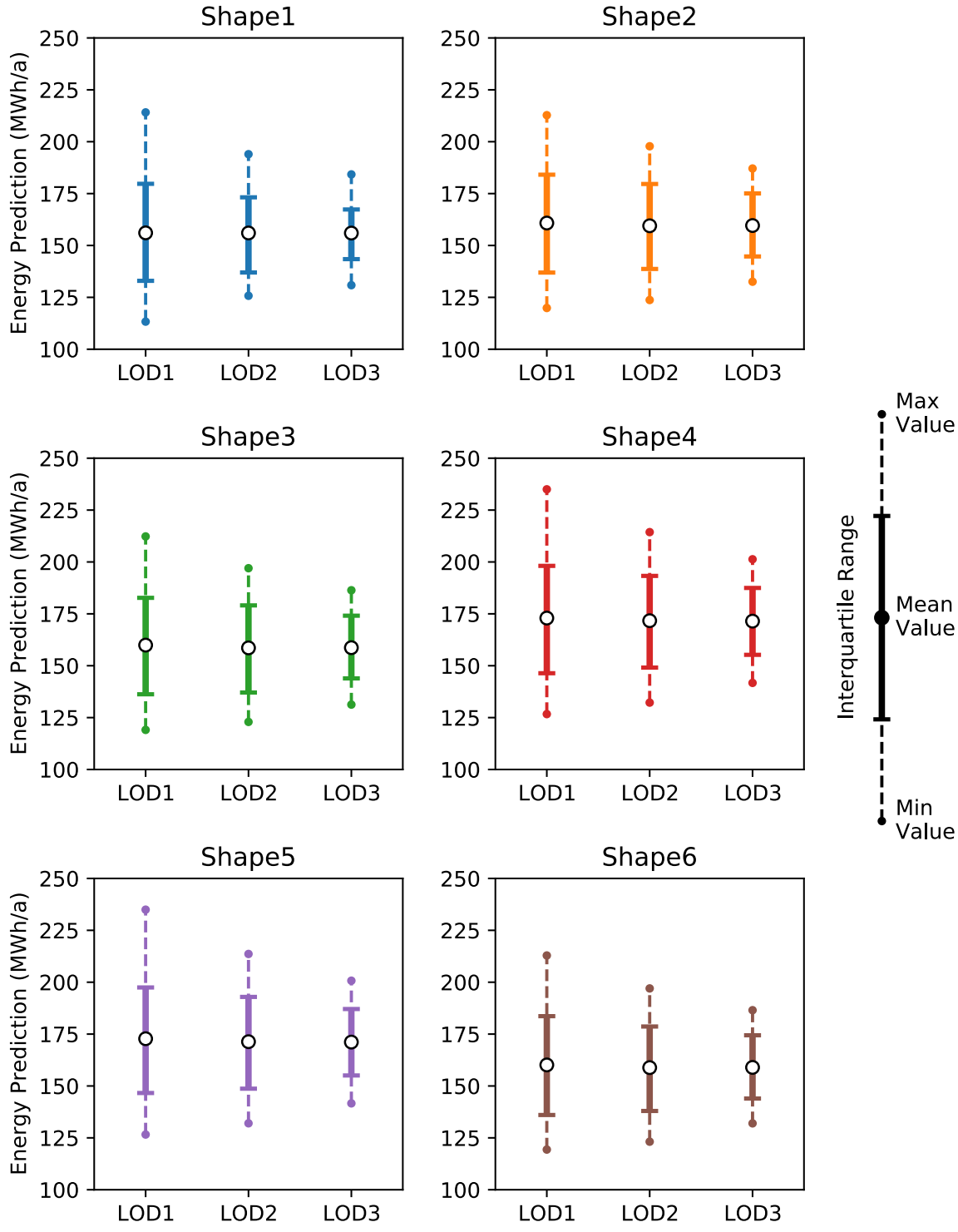

Figure 2.7 Effect of the level of uncertainty on the performance prediction

Assuming that suitable values to the design parameters are assigned following the order of preference, it should reduce the maximum uncertainty at LOD 1 by fixing the geometrical parameters, followed by fixing technical specification at LOD 2, and window parameters at LOD 3. This assumption is tested by assigning values to the design parameters and observing its effect on the uncertainty in energy prediction at each LOD. The energy use is predicted using the mean values of the design parameters and random combinations of the uncertain design parameters at each LOD. The energy prediction results are plotted in Figure 2.7 for each shape. The dot shows the mean value, the solid line shows the inter-quartile range, and the dashed line shows the range of energy predictions. Both the range and interquartile range (IQR) are used to assess uncertainty in the predictions. It can be noticed the uncertainty in energy predictions reduces as uncertain parameters are assigned with a fixed value. The uncertainty as LOD 1 is highest, followed by LOD 2, and LOD 3. For example, in Shape1, the mean value of energy prediction is 156 MWh/a, ranges at Level 1, 2 and 3 are 100 (65%), 68 (44%), and 53 (34%) respectively. The IQRs at the same levels are 23 (15%), 18 (12%), and 12 (8%), respectively. The same trends are observed for Shape 2 to 6.

5. Discussion

Using the variance based sensitivity analysis, the parameter and their groups are ranked in the order of their influence on the predicted energy use. It has been shown that the reduced uncertainty in design parameters allows a more precise prediction of the energy performance. Moreover, it is important to identify influential parameters as finding a suitable value for these parameters reduces the uncertainty more than the others. However, designers will prefer to focus of a combination of parameters at each LOD which makes the uncertainty contribution by parameter groups more relevant to form the basis of information requirements at each LOD in the multi-LOD approach.

The first order effects and parameter ranking indicates that Permeability, Height, Width, U-value (window), Length, Operating Hours, Boiler Efficiency, g-value, and U-value (wall) are the most influential parameters. The ranking of these parameters based on All Shapes represent their order of influence in early design stages as it is calculated over several architectural designs. The remaining parameters have the first order effects of less than 0.01, suggesting that their uncertainty contributions are very small in predicting the energy use. It should be noted that the ranges of all the parameters only varies ±25% from the mean value. Due to non-linearity, these results cannot be generalised if a higher range is defined.

Sum of the first order effects for the first nine influential parameters is close to 0.93, which means 93% of uncertainty can be removed by finding the value of these nine parameters. However, it is not logical to focus on these parameters at one level, as the nature of these parameters is completely different. For example, a designer cannot focus on Length and Width with U-value (window). The first order effect of Length, Width, and Height is close to 0.4, which means 40% of the uncertainty can be removed just by assigning a suitable value to them.

There is no significant change in the parameters' sensitivities across the geometrical shapes. Therefore, the sensitivity analysis results can be generalised for the multi-LOD approach to determine which information best serves to reduce uncertainty in the model outcome at the early stages. The parameter groups are divided into three levels which causes more than 40%, 20%, and 10% variance in the model outcome, i.e., predicted energy use. Designers should prioritise finding a suitable value for geometrical parameters at the first level as it causes most part of the uncertainty. In the next level, technical specifications should be focussed, followed by window parameters at LOD 3. The operational design and equipment efficiencies may remain uncertain after the design that will cause around a total of 14% variance in the predicted energy demand.

It should be noted that the variance based sensitivity analysis method provides sensitivity indices of comparative nature, i.e., the influence of a parameter with respect to all the parameters under consideration. Thus, the results cannot be used to interpret the effect of one parameter if other parameters do not have the mentioned uncertainty range. There are some parameters such as WWRs, permeability, and lighting and equipment heat gains which may not be possible to define in the range of ±25% at the early stages. In that case, the method can be used to compute the uncertainty contribution for new ranges and determine the information required to predict the energy use.

A typical office building in Munich as a test case has been examined in the article. The weather plays a significant role in energy predictions and affects the parameters' sensitivities; thus, the results cannot be generalised for another location without further tests. To make the sensitivity analysis results still more generalisable for the early stage of design, the different building shapes of the comparable area with varying length and width have been included in the analysis. The parameter space has a variation of ±10% for geometrical parameters and ±25% for other parameters, and the sensitivity analysis results are only applicable in the defined ranges. The building energy model considers the effect of self-shading only. The effect of shading from the surroundings or overhangs isn't studied in the article, which is expected to influence the energy prediction. As the article focusses on the early stage BEMs, the energy system is represented by equipment efficiencies, only.

6. Conclusions

The ranking of design parameters is useful for the identifying information required to make precise energy predictions and prioritise design decisions from the energy perspective. There is very little change in the sensitivities of design parameters across different building shapes. Thus, the parameters' sensitivities are generalised for the early stage building energy models. The uncertainty contribution by a group of parameters is more relevant for identifying information required at every level-of-development (LOD). It is possible to identify three levels of uncertainties corresponding to three levels of the multi-LOD approach. A designer shall start the design process with a rough definition of all the design parameters in a typical multi-LOD

approach, i.e., defining parameters with a mean value and range of ±10% for geometrical parameters and ±25% for other parameters. Afterwards, the designer should focus on the design parameters in the following order of preference – geometrical parameters (LOD 1), technical specifications (LOD 2), and window parameters (LOD 3). In a broader context, the article proposes the sensitivity analysis method to identify the most relevant design parameters for performance based design. The parameters are grouped based on their nature and uncertainty caused by parameter groups is ascertained. The parameter groups are focussed based on the order of their ability to reduce uncertainty in the performance prediction. Thus, it will form the basis to define the information requirement at each level of development.

************* (*end of the published article*) *************

Annexure A. Annexure to Chapter 2

The annexure discusses the published article's findings within the doctoral research context. The chapter focusses on the objective:

- To define the information requirements at each level of the multi-LOD approach for predicting the probabilistic energy use.

The chapter used the variance based sensitivity method to calculate the first-order effect of parameters. The information required at each LOD is defined based on the premise that the first-order effect represents the uncertainty caused by an uncertain parameter in the energy predictions. Thus, the first-order effect for any parameter represents the part of uncertainty that can be removed by fixing its value. In the variance based method, uncertainty in the model outcome is represented by its variance. Hence, the first-order effect estimates the part of variance associated with an uncertain parameter. The variance in the model outcome for Shape 1 is analysed to assess this statement. The total variance in the model outcome is 326 sq. MWh/a at the beginning. All the parameters are uncertain and randomly distributed in the defined ranges at this LOD, as mentioned in Table 2.1. After fixing the values of geometrical parameters at LOD 1, the variance reduces to 188 sq. MWh/a at LOD 2. The reduction in variance from LOD1 to LOD2 is 42%, close to the uncertainty contribution of 44% for geometrical parameters calculated using the sensitivity analysis method. Similarly, from LOD 2 to LOD 3, the variance reduces to 102 sq. MWh/a after fixing technical specifications. The total reduction in the variance is around 69%, compared to 66% at LOD 3, calculated using the sensitivity analysis method.

Limitations of the test case, energy model, and parameter selection

The chapter used a test case to estimate the uncertainty contribution by parameter groups and concludes that geometrical parameters cause the maximum uncertainty (around 43%), followed by technical specifications (around 25%), and window parameters (around 14%). The remaining parameters cause around a total of 14% of the uncertainty. The limitations of these results arise from the question to which extent the test case represents the early stages. The following limitations must be considered while generalising these results:

1. The chapter considered that all parameters are defined by minimum and maximum values at the beginning of a design. All the parameters (except geometrical) are assumed to have mean values ±25% range. However, geometrical parameters are considered in mean values ±10% range to keep the floor area in an acceptable range. Hence, the value of uncertainty removed must be interpreted with these assumptions of uncertainties in the design parameters. Further as highlighted by [28], a more accurate distribution of parameters needs to be considered for a better estimation of uncertainty in the energy predictions.
2. Some building characteristics are represented by simple parameters to ease developing the simulation models. For example, operating hours and heat gains represent building

operation. A more elaborate representation of building operation using schedules will allow more realistic energy predictions. However, it requires significant modelling efforts and may not be useful in the early stage design context.

3. Similarly, U-values and solar heat gain coefficients represent thermal properties of construction components. More sophisticated energy models can be developed to perform more realistic energy simulations. Such as, construction components can have more parameters like heat capacity, solar absorptance, visible transmission, etc. However, the chapter assumed a fixed value for these parameters to limit the number of design parameters and simplify energy modelling.
4. The study assumed only one type of energy system to provide heating and cooling, represented by the parameters - boiler efficiency and coefficients-of-performance. More diverse systems can be considered to study their effect on the uncertainty of energy predictions. On-site and renewable energy generation is another aspect that will influence the uncertainty in energy predictions.
5. The chapter also assumed mostly numerical design parameters such as U-values, air permeability, etc. However, early stage decisions also involve yes/no decision such as whether to use under floor heating, night ventilation, internal shading, or movable external shading. Such decisions affect the energy predictions; hence, their presence or absence will cause uncertainty in the predictions. It is possible to study the uncertainty due to such design decisions using the variance based method. However, it will require to generate energy models with and without these design features, which is a cumbersome task.

Conclusions with respect to the doctoral research objectives

The chapter defined the information requirements at three levels of development (LOD) of the multi-LOD approach based on engineering knowledge. The underlying assumption is that designers focus on reducing the uncertainty in energy predictions through design development. Based on the sensitivity analysis results, the chapter concludes that if geometrical parameters are defined within the range of a mean value ± 10%, technical specification, window construction, building operation, and equipment efficiencies within the range of a mean value ± 25%; the geometrical parameter will cause the uncertainty (variance) of more than 40%, followed by 20% by technical specifications, and 10% by window parameters. These findings conclude that geometrical parameters are of prime importance at LOD 1, technical specification at LOD 2, and, finally, window construction parameters at LOD 3. The remaining parameters may remain uncertain after the design, but their uncertainty could be reduced if required to provide more precise energy predictions at the early stage.

3

Data increment and enrichment for training ML models

Chapter 3.
Data increment and enrichment for training ML models *

General introduction

The chapter focuses on developing a machine learning (ML) model for early stage energy predictions. Utilising the concept that more training samples improve the model generalisation, the chapter develops an efficient approach to collect new training samples. It contributes to improving the ML model generalisation by answering the following questions:

? What is the effect of different training samples on the model generalisation?

Most of the ML development for building energy prediction focusses on parametric features such as U-values, air permeability, and thermal mass, with only little importance given to building geometry [38,46,64]. Even though, several factors affect the building geometry besides energy performance, an ML model that generalises for different geometries is required

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The general introduction and annexure were not part of the published article and have been added to align its findings with the doctoral research objectives. Minor corrections have been made to the published article to address comments of the PhD committee.

The doctoral researcher has conceptualised, developed methodology and software tools, developed and trained machine learning model, conducted formal analysis and investigation, visualised the results, and written original draft and revisions. The remaining authors have helped in conceptualisation, visualisation of the results, and writing the article.

so that it can predict the energy use for any changes made to the building geometry. Hence, the chapter focusses on the geometry of early stage design configurations.

The building geometry has been identified as a major challenge to developing ML models for energy prediction as the geometrical characteristics are difficult to be described by a set of parameters [47,94]. The geometry is a non-parametrised feature of buildings which makes both collecting samples and training ML models a difficult task. Researchers developed the approach of component based ML (CBML) to train an ML model for predicting energy demand of early stage design configurations [47]. CBML approach trains reusable ML components that can predict the energy use of several building geometries, structurally varied beyond parametrisation. The chapter extends the CBML approach to predict the total energy use, incorporating equipment efficiencies.

ML models require significantly different training samples to learn from the data. While it is to quantify diversity of samples based on numerical features such U-values, assessing diversity based on the building shape requires advanced data analysis methods. The chapter develops a method to quantify the diversity of samples based on the shape using principal component analysis. Diverse training samples have a higher ability to improve the model generalisation than similar ones. Hence, new samples should be different from the existing samples to create large dataset to improve the model generalisation.

The chapter proposes data increment and enrichment as two potential approaches to collect new samples. While the increment approach uses the energy model of a box-shaped building of varying dimensions to collect new samples, the enrichment approach uses differently shaped building samples. The base case dataset consists of 200 samples, and 200 samples are added at each increment and enrichment step. The exercise has been repeated to create three increased and three enriched datasets. The increased and enriched datasets have been analysed to study the difference between the diversity of the samples. The research trains ML components and calculates the generalisation errors corresponding to the training datasets. The findings conclude how different training samples affect the model generalisation and which data collection approach is better to improve the model generalisation.

Machine learning for early stage building energy prediction: Increment and enrichment

Abstract – Collecting data for machine learning (ML) development is a resource-intensive task that necessitates identifying an efficient data collection approach. The article develops ML models to reduce the computational expensiveness of the early stage energy predictions. The generalisation of such models for multiple building shapes is vital to predict energy demand at the early stages. Therefore, the article examines which approach of collecting new training samples improves the generalisation more - increment of samples of the same shape or enrichment with samples exhibiting novelty in shape. The first training dataset collects samples from a box-shaped building energy model (BEM). Distribution analysis suggests that they fill only a small portion of the design space. Using the same BEM, the increment approach collects samples of varying dimensions that fill the same portion. In contrast, using three differently shaped BEMs, the enrichment approach collects samples well-distributed in the design space. The distribution of samples in a training dataset is quantified to assess their potential to improve generalisation. Using the same number of training samples, the enrichment approach fills the design space better than the increment, reducing the generalisation error (root-mean-square-error) by 58%, compared to 38% after the increment. Hence, the article suggests analysing the distribution of existing and prospective samples to identify an efficient data collection approach having a higher potential to improve generalisation. The developed method will be useful to save expensive data collection resources by focussing on a limited number of samples.

Keywords: energy performance; data collection; training data; generalisation error; data analysis.

1 Introduction

The energy-efficient building design is essential to address global energy concerns and fulfil regulatory requirements [95]. Additionally, in the early stages, decisions related to energy performance are the most effective at the lowest costs for changes [9,31]. A designer analyses and compares several design options, primarily using the rules of thumb during an exploratory design process [96]. Building performance simulations (BPS) are used to predict energy performance and make such comparisons based on reliable information [18,97]. However, uncertainty in the design information requires simulating several building energy models (BEMs) to obtain BPS results for energy prediction [28] and decision-making [98,99]. The computational expensiveness renders dynamic energy simulation tools impractical at the early stages and calls for computationally inexpensive metamodels or engineering-surrogate models [52].

Machine learning (ML) approaches are used extensively to approximate the input-output relationship exhibited by complex BEMs and develop simplified metamodels [100,101]. ML models provide quick BPS results at a slight loss of accuracy, representing a deliberate trade-off between computational time and accuracy [102]. Since the information available at the early stages is limited and uncertain, the objective of BPS is to compare and classify several options than precise energy predictions [13]. This objective makes time-efficient ML models suitable at the early stages [103]. However, it requires developing an ML model that predicts the energy use of various design configurations. Hence, the article develops an ML model to substitute simulations at the early stages and focuses on improving its generalisation, i.e., prediction accuracy on cases different from the training data.

Early stage BEMs are characterised by various design configurations that include different shapes and a wide range of technical specifications. The challenge is to develop an ML model that captures complex interactions between geometry and technical specifications, well. The use of large training datasets to improve the generalisation is illustrated for other ML applications. However, BEMs have a few domain-specific complexities, such as the hierarchical structure of building components, non-linear interactions among parameters, transient thermal behaviour, and complex geometrical representation. These complexities separate BEMs from other ML applications; hence, it requires investigation into data collection approaches to improve the generalisation. The article examines how extending the training datasets—increasing or enriching—improves generalisation. Besides highlighting the need to improve distribution to improve generalisation, the article proposes a method to identify diverse samples based on non-parametric feature, building shape. Further, it identifies an efficient data collection approach in the context of early stage BEMs.

1.1 Size of training dataset and the ML model generalisation

ML model generalisation refers to its ability to make accurate predictions on unseen data, i.e., the samples not used in the training process. A few methods to improve the generalisation are large training datasets [63,104], feature engineering [46], appropriate learning algorithms, and hyperparameter tuning [64]. The recent developments in ML algorithms and computing resources allow ML models to learn from large datasets [62], making data a vital ingredient to developing ML models. While training ML model on the data is domain independent, it requires domain knowledge to collect training and test samples. Hence, the article focusses on collecting representative training samples for developing ML models.

[105] has shown that increasing training data improves the accuracy of predictions. In ML applications to image classification [106] and language processing and translation [107], training data volume improves accuracy, significantly. [108] has shown that the size of training data improves the accuracy of ML based energy predictions. The efficiency of several ML algorithms has been studied for different sizes of training datasets. These studies show that the model generalisation improves with the size of the training dataset irrespective of its learning

algorithm. However, collecting new samples requires resources. Researchers studied the influence of a training sample on the prediction accuracy to analyse anomalies in the training dataset [109]. The study highlights that not all training samples are useful for improving the generalisation. However, its use in identifying prospective training samples that are useful to improve generalisation is not studied.

Sampling schemes such as Latin hypercube [110] or Sobol [111] optimises the distribution of samples in the design space to capture parameter interactions [112,113]. Similarly, datasets with diverse training samples capture relevant parameter interactions and allow training a well-generalising ML model [114]. However, data collection approaches to collect diverse samples are specific to the domain. For example, in speech recognition, voice samples of different accents were collected to improve generalisation [115,116]. A similar data augmentation approach is used to improve the accuracy of text recognition [117] and image classification [118]. [39] has used the data from several locations to train energy prediction models for different climatic zones.

Previous studies suggested that both large training datasets and diverse training samples are essential to improve model generalisation. Since data collection approaches are domain-specific, it requires investigation into potential approaches for early stage building energy prediction. Moreover, collecting new samples is a resource-intensive exercise making it imperative to identify an efficient data collection approach that improves the generalisation with a limited number of training samples. By analysing the distribution of prospective training samples, the article identifies an approach that has a higher potential to improve the generalisation.

1.2 State-of-the-art approaches to develop metamodels for energy predictions

Designers develop a building mass model in an uncertain scenario at the early stages [119]. Hence, it requires an ML model that accurately predicts energy performance for various design configurations, including different shapes [120]. Previous works developed metamodels (using ML or other approaches) for a fixed building geometry or rectangular shape of flexible dimensions [79,121], which are not suitable for the early stages. [45], [46] , and [122] developed simple parametric metamodels, representing building shape by a parameter, such as compactness. A simple geometrical representation and parametric ML definition do not capture dependencies between geometry and thermal behaviour, well. [47] proposed a component based machine learning (CBML) approach based on the decomposition of design artefact into components. It is flexible enough to adapt to new design cases without changing the model structure or re-training the ML components. Therefore, CBML is used as an exemplary approach to developing the ML model for the early stage energy predictions. More details of CBML are provided in subsection 2.3.

Previous studies used a box-shaped BEM to collect samples for training CBML components. However, the samples from only box-shaped BEM are insufficient to capture the data diversity of the test samples that have different shapes. It results in a loss of accuracy for design cases outside of the training data [94,123]. [42,44] explained the well-generalising behaviour of a deep learning model based on its ability to identify the similarities between training and test samples. The usefulness of differently shaped BEMs that allow collecting diverse training samples has not been studied to improve the generalisation. Hence, an investigation is required whether the training samples from differently shaped BEMs are diverse enough to capture the diversity of test samples and improves the generalisation for early stage energy predictions.

1.3 Problem statement and research objectives

The approach of CBML to develop an early stage energy prediction model requires better generalisation for different shapes. Studies from other ML applications argued that large training datasets containing diverse samples improve generalisation. Since approaches to collect new samples are domain-specific, it requires investigation into data collection approaches for the energy prediction model. Moreover, it lacks a method to identify new training samples that have a higher potential to reduce the generalisation error than others. The lack of such a method requires expensive data collection efforts that will improve the generalisation only a little. Hence, the article investigates two data collection approaches and proposes a method to identify training datasets with a higher potential to improve generalisation using data analysis. An efficient data collection approach, focussed on improving the generalisation, requires collecting samples that are different from the existing samples and well-distributed in the design space. The article develops a method to identify diverse samples and quantify their dispersion based on its shape. It measures the distribution of training samples by standard distance distribution, i.e., the Euclidean distance among the samples of multivariate data [124]. A higher distance between two samples signifies that the two samples are different, and the corresponding training dataset have well-dispersed samples [125].

The early stages are characterised by different building shapes and uncertain technical specifications. The building shape is of particular interest in the article, structurally varied by components beyond parametrisation. While previous studies focus more on parametric technical specifications, the article focuses on shape variations at the early stages. However, a relevant range of technical specifications is also considered to capture its interactions with the shape. Since the building shape of BEM is not parameterised, it requires a novel approach to collect diverse training samples. The article uses BEMs of commonly used building shapes to collect new training samples. A BEM of a basic architectural shape, box-shaped, easy to create and requires minimal resources to simulate, is used to collect samples for the first training dataset. A few more samples from the same box-shaped BEM are collected, by varying the parameters, including geometrical, to create increased datasets. This approach of collecting new samples refers to data increment and expected to increase the number of samples with a minor improvement in the distribution. Contrary to the increment approach, more samples are

collected from differently shaped BEMs to create enriched datasets, which requires additional efforts to create new BEMs. This approach of collecting new samples refers to data enrichment and expected to provide diverse samples. The ML models are trained on multiple increased and enriched datasets to assess their ability to improve generalisation. Besides developing an ML based energy prediction model for early stage design configurations, the article –

a) Develops a method to identify training datasets that have well-distributed samples and allows a higher improvement in the generalisation.
b) Develops an efficient method to get well-distributed samples across the design space in the early stage BEM context.
c) Compares two data collection approaches based on their ability to improve the distribution of training samples and the ML model generalisation.

The remaining article is organised into four sections. Section 2 describes the methodology for defining the design space for the early stage context, approaches to collect new training samples, and the component based ML model structure. Section 3 documents the findings of the article, i.e., changes in the distribution of samples and the corresponding changes in the model generalisation using increment and enrichment approaches. Section 4 discusses the transferability and limitations of the proposed approaches to improve generalisation. Section 5 provides conclusions and the utility of data enrichment in a broader ML context.

2 Research methodology

The research methodology is described in three subsections. The first subsection provides details of the design space and data collection. Section 2.2 describes the data collection approaches and a method to analyse the distribution of training samples. Section 2.3 documents the component based approach for training the ML model.

2.1 Definition of design space, generalisation errors, and data collection

The article develops an ML model for a typical medium-size office building in Munich as an example. The design space is defined by the parameters, mentioned in Table 3.1. The selection of these parameters and their ranges is based on previous studies, relevant German standards for energy-efficient design, and typical characteristics of office buildings [22,25,126]. The ranges of parameters are only exemplary to demonstrate the proposed approaches and small changes in their values is unlikely to affect the accuracy of ML models. Moreover, both the data collection approaches use the same parameters' ranges for generating samples; hence, their selection will not affect the findings. However, these parameters are relevant to study their possible interaction with the building geometry. Constant features of the BEM, such as ventilation, schedules, and building operations are descibed in Appendix A. The design space represents possible variations in the building shape, too; a few of them are shown in Figure 3.1. These random shapes have different floor areas based on the sampled value of floor area. Random shapes are generated by arranging squares of variable dimensions, as explained in

Appendix C. The samples have different floor area, based on the sampled value of the parameters, floor area. The article uses a test dataset consisting of 200 randomly generated samples in the design space to estimate generalisation errors. The design parameters, mentioned in Table 3.1, are sampled using the Latin hypercube sampling scheme for the test dataset [110]. We used three measures to estimate the generalisation errors - root-mean-square-error (RMSE), coefficient of determination (R^2), and mean-absolute-percentage-error (MAPE). RMSE and R^2 are second-order measures, sensitive to high-range values, while MAPE is a measure of the first order, sensitive to low-range values [127]. The measures of two different orders ensure that the reported errors are relevant for the entire range of predictions. Further, the model generalisation is expressed by scatter plots and error histograms.

Table 3.1 Parameters for the design space and test building

Parameters	Unit	Min	Max	Parameters	Unit	Min	Max
Floor Area (each floor)	m^2	250	600	WWR [1]	-	0.2	0.8
Floor-to-floor Height	m	3.0	4.0	Internal Mass	kJ/m^2K	60	150
No. of Floors	-	3	5	Air Permeability [2]	$m^3/h{\cdot}m^2$	6	9
Orientation	°	0	45	Operating Hours	h	8	12
U-value (Wall)	W/m^2K	0.15	0.35	Occupant Load	m^2/Person	15	20
U-value (Ground Floor)		0.15	0.35	Light Heat Load	W/m^2	4	10
U-value (Roof)		0.15	0.35	Equipment Heat Load		4	10
U-value (Window)		0.6	1.0	Heating COP	-	2	5
U-value (Internal Floor)		0.2	0.5	Cooling COP		2	5
g-value	-	0.4	0.8	Boiler Efficiency		0.85	0.95
Heat Capacity (Slab)	kJ/kg K	0.8	1.2				

[1] WWR vary independently in each direction.

[2] The infiltration rate is calculated by $(0.07\times\rho\times A/0.8\times V + 0.1)$ air changes per hour (ACH), as illustrated in EnEV (German) standard 18599. 0.07 is volume flow coefficient (standard value as per DIN EN ISO 13789), ρ is air permeability at 50 pascals, A is total surface area, V is the external volume, and 0.8 is a factor to calculate net volume from external volume. 0.1 is added to account for infiltration through windows.

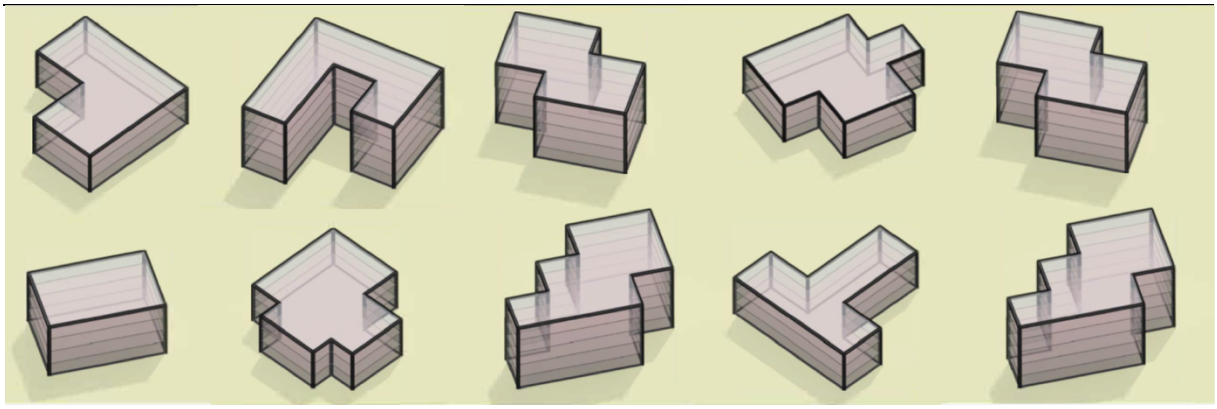

Figure 3.1 Random building shapes for the test building

It requires a large number of samples to train and test the ML model. Since collecting so many samples from actual buildings is impractical, a dynamic energy simulation tool - EnergyPlus, has been used. An EnergyPlus model has been developed for the building, 'Tausendpfund' [89]. The heating and cooling energy demands were recorded for two years. The simulation model has been calibrated using the measured energy consumption, and Appendix A documents these findings. The design parameters are modified to generate an energy model for each sample. Other relevant details such as weather, thermal zones, and indoor climate are provided in the appendix. It also provides the details of isolation values for self-shading building shapes. In the article's context, the enregy use accounts for energy required by heat pump and electric boiler to provide heating and cooling, only.

2.2 Approaches to collect training samples and their effect on the distribution

We are studying different approaches to collect new samples that improve the ML model generalisation. Therefore, we need to start with a small number of samples and gradually increase the number of samples. We arbitrarily chosen 200 samples for the first dataset and will add 200 samples to the dataset in each step. The first training dataset consists of samples from a box-shaped BEM, referred to as the base case. It has 200 box-shaped building samples of varying dimensions, described by Shape 1 in Figure 3.2 and Table 3.2. Besides, the shape, length, width, and floor height represents the building geometry. Except for length and width, all the design parameters have the same range as the test dataset, mentioned in Table 3.1. Sobol sampling, a quasi-random sampling scheme, is used to sample the parameters for training datasets. This sampling scheme ensures a uniform distribution of samples in a parametric space [111].

Table 3.2 Range of building dimensions for Shape1, Shape 2, Shape 3, and Shape 4

		Shape 1		**Shape 2**		**Shape 3**		**Shape 4**	
	Unit	Min	Max	Min	Max	Min	Max	Min	Max
Length	m	16	20	18	24	18	25	18	26
Width		16	20	18	24	18	25	18	26

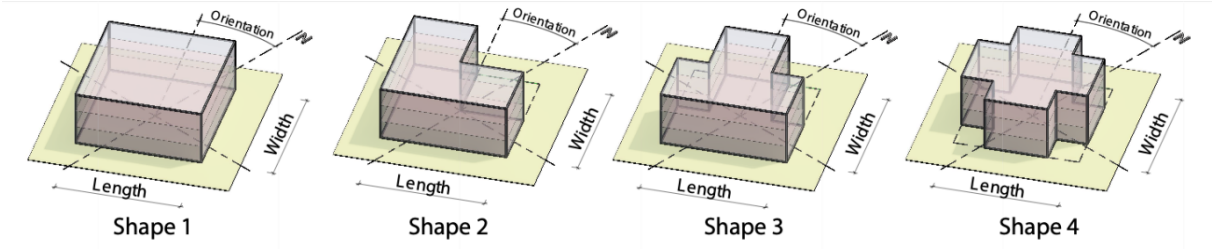

Figure 3.2 Building shapes used in training datasets

Distribution of training samples in the design space

Since the article focuses on the shape characteristics, the ranges of other design parameters, such as U-values, are kept the same for all the training datasets (Table 3.1). The samples in the training datasets differ only based on the shape. Hence, the distribution of training samples is

analysed based on the shape to identify vacant spaces in the design space. Since all floors in a sample are the same as ground floor, the building shape can be represented by its footprint. We used a 20×20-pixel black and white image to represent the building footprint. Each pixel is equivalent to 2.5 m. and has a value of either 0 or 1 to represent a black or white pixel, respectively. Black pixels represent the building, while white pixels represent the empty space. Thus, a sample, based on its shape, is represented by 400 (20×20) dimensions/features. The visualisation of samples for such a multivariate dataset requires dimensionality reduction. Dimensionality reduction techniques extract important features to improve interpretability while minimising information loss [128].

Principal component analysis (PCA) is a statistical approach for identifying principal features based on the total variance [129]. It transforms the data to a new coordinate system such that the first axis of the new coordinate system captures the maximum variance, followed by the second and so on; thus, referring the direction of the first axis to the first principal component and so on. The exercise of dimensionality reduction using PCA captures the maximum variability along with a few principal components. A detailed explanation about the principal component analysis for images, its intuition, and its use in the article has been provided in Appendix D. Using PCA, the dimensionality of a sample image has been reduced from 400 (20×20) dimensions to two dimensions to allow visualising the samples in a two-dimensional space. Figure 3.3 shows some building shapes from the design space and the base case dataset, and Figure 3.4 shows the distribution of these samples in the design space. Principal components are calculated based on the samples from the design space that are used to transform all the datasets for visualisation. Both Figure 3.4 and Figure 3.6 use the same PCA transformation and scale for the principal components.

Standard distance deviation (SDD) quantifies the distribution of samples for multivariate data. SDD is the average of Euclidean distances between the mean sample and training samples expressed by Eq. (1). The mean sample is calculated by taking the mean along each dimension of multivariate datasets. A black dot in Figure 3.4 and Figure 3.6 shows the mean sample. It should be noted that SDD does not include the effect of the size of the training dataset. Hence, the article uses m×SDD (mSDD) to measure the distribution, where m is the total number of samples in a training dataset. Hence, mSDD represents the total of Euclidean distances between the samples and their mean. D_i is a Euclidean distance between the mean sample and i^{th} training sample, as shown by grey lines in Figure 3.4 and Figure 3.6. A higher value of mSDD signifies the dissimilarity among samples or a better distribution of samples across the design space.

$$DD = \frac{1}{m}\sum_{i=1}^{m} D_i\,; \qquad mSDD = \sum_{i=1}^{m} D_i \qquad \text{... Eq. (1)}$$

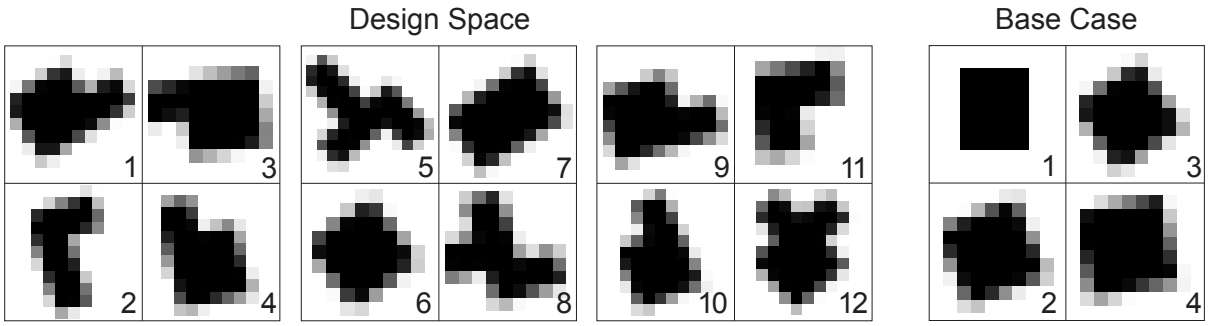

Figure 3.3 Building shapes from design space and base case dataset

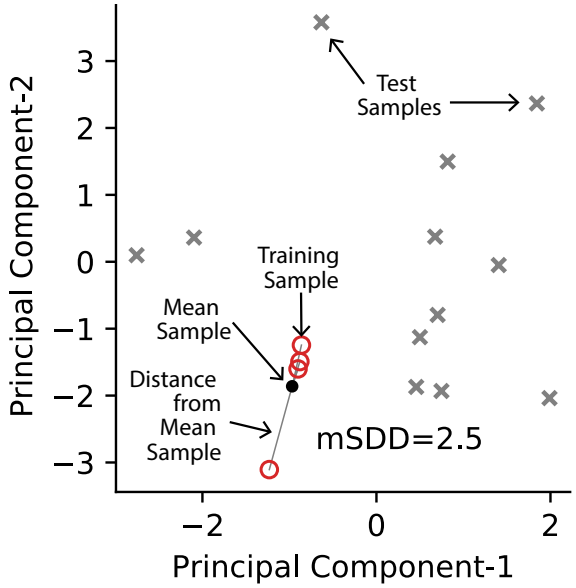

Figure 3.4 Distribution of training samples from base case dataset

Figure 3.4 shows that the base case dataset has too many vacant portions, which implies that the training samples do not reflect the design space variations. Therefore, the article investigates data collection approaches that provide training samples to fill the design space. Since the article aims to collect well-dispersed samples to improve ML model generalisation and well-dispersed samples are characterised by a high mSDD value, a better training dataset is identified by a higher value of mSDD.

Data increment

The first approach to collect samples is data increment that uses the same box-shaped BEMs. This approach requires only a little effort as the same BEM with parametric capabilities is used to collect new samples. We created three increased datasets, I-1, I-2, and I-3, having 400, 600, and 800 samples, to study its effect on the generalisation errors. Figure 3.5 shows a few samples from the increased datasets, and Figure 3.6 shows their distribution and ability to fill the design space. The new training samples are close to the existing samples, increasing mSDD to 11.7 units for 16 samples.

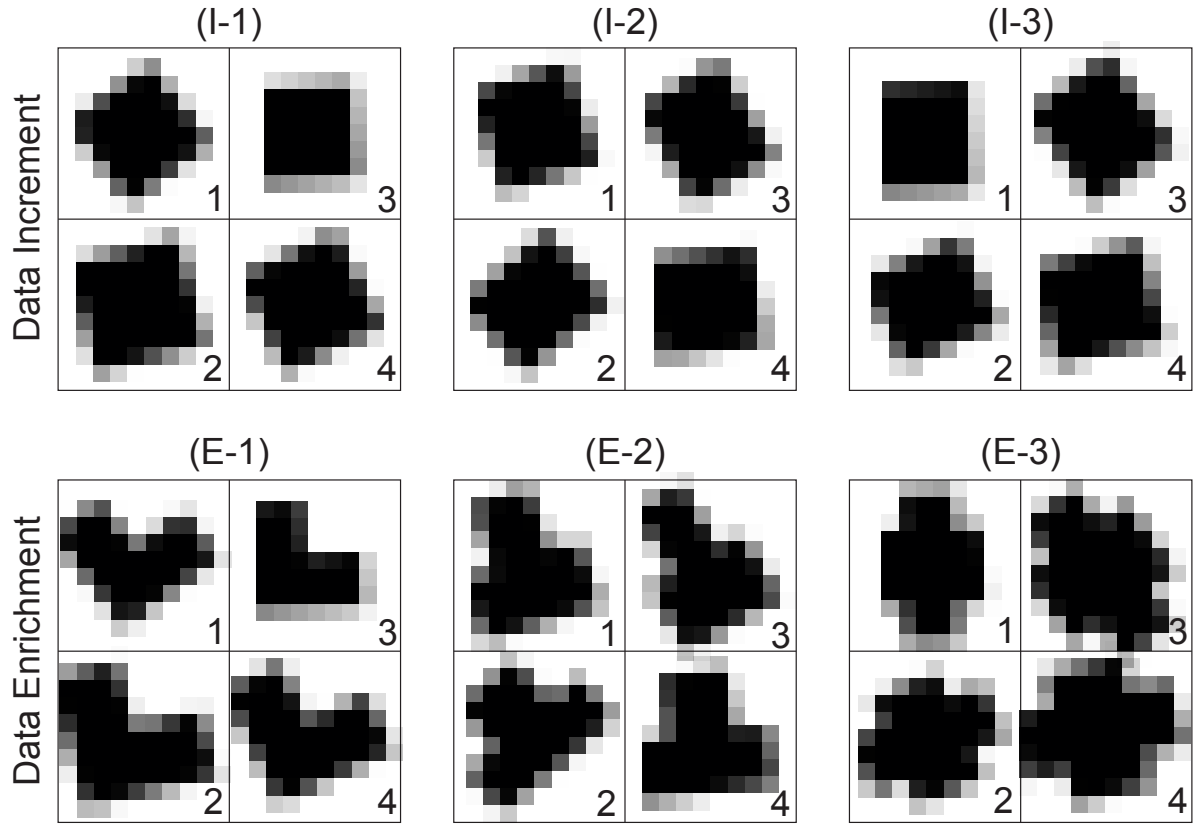

Figure 3.5 Building shapes from increased and enriched datasets

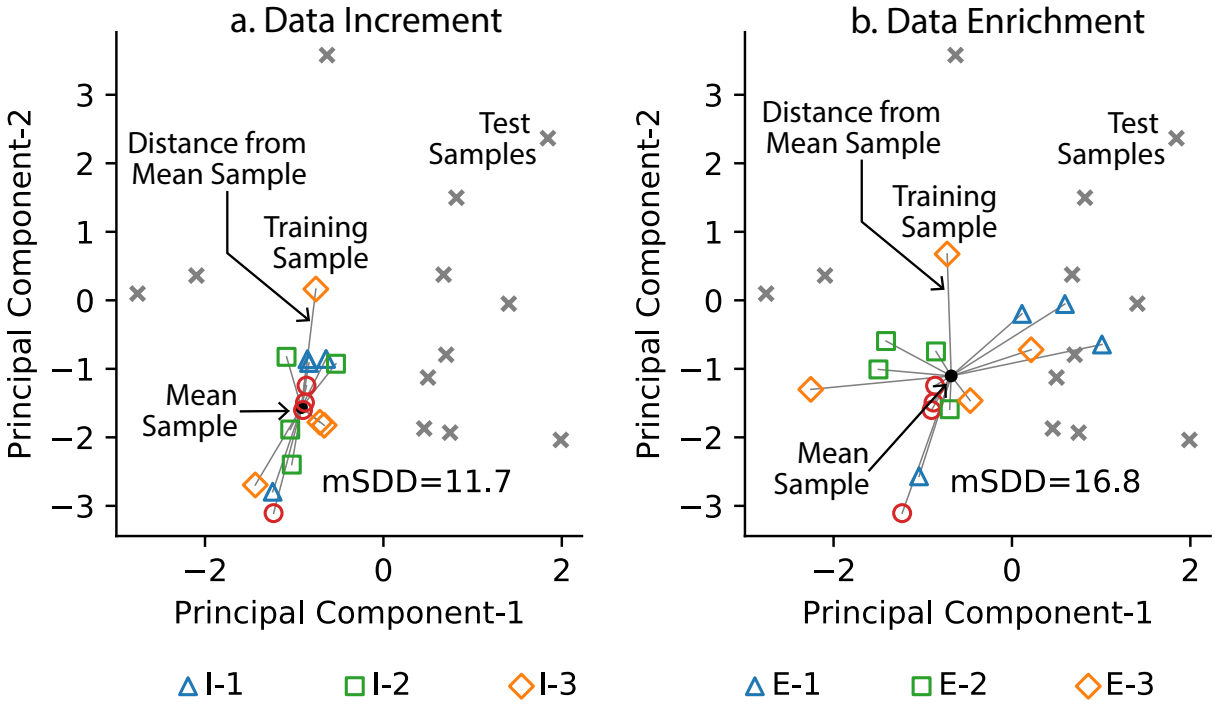

Figure 3.6 Distribution of samples from increased and enriched datasets

Data enrichment

A few more samples are collected from differently shaped BEMs to create 'enriched' datasets. Additional simple shaped BEMs – Shape 2 (L), 3 (T) and 4 (plus), commonly used shapes in office buildings [87,88], are used to collect new samples. The details of these shapes are provided in Figure 3.2 and Table 3.2. This approach requires additional efforts to create new BEMs and more simulation time than box-shaped BEM. 200 samples are collected from BEM of each shape, resulting in 400, 600, and 800 samples for three enriched datasets, E-1, E-2, and E-3, respectively. The dimensions are also increased slightly for Shape 2 to 4 to include its effect. Few samples from enriched datasets are shown in Figure 3.5, and their ability to fill the design space is shown in Figure 3.6. The new training samples are better distributed than the increased datasets, increasing mSDD to 16.8 units for 16 samples.

The ML components are trained on the base case, increased, and enriched datasets to assess how the model generalisation changes with different data collection approaches. The values of mSDD and the generalisation errors are compared for different training datasets to find a correlation between them.

2.3 CBML approach for developing an early stage energy prediction model

The article uses component based machine learning (CBML) as an exemplary approach for training an ML based energy prediction model. The approach overcomes the limitations of parametric modelling. It relies on the organisation of components to represent complex building geometries. CBML follows an approach of decomposing an energy model into components based on design and engineering information. Following the structure of an energy model, it assumes a building is composed of zones. The zones are composed of construction components such as floors, walls, windows, and roofs. There is an ML component corresponding to each element to represent its thermal behaviour. A new building shape is developed by composing these elements, as required. Besides representing complex building shapes, CBML has the benefits of interpretability, transferability of trained components to new design cases, and integration into the existing data structures, which has been discussed extensively in the mentioned references [47,66].

The article uses the CBML model structure, as shown in Figure 3.7. The decomposed ML model structure allows the transfer of representations learned from simpler building shapes to complex building shapes [48]. In simpler words, the CBML approach allows training ML components that can predict the energy performance of building shapes different from the training dataset. However, ML components trained on only box-shaped BEM are not able to capture the interaction between the building shape and its energy performance. By comparing the increment and enrichment approach, the article discusses the effect of diverse-shaped training samples on the generalisation of ML components for complex structures and improvement in the accuracy of predicted energy demand. There are ML components at three levels - element, zone, and building. The element level models are heat flow models for wall &

window, ground floor, roof, and infiltration. Area, thermal heat transfer coefficient (U-value) and heat capacity are used as input for heat flow models. Orientation and solar heat gain coefficient (g-value) are used additionally for wall & window heat flow components. The infiltration heat flow, caused by leakages and cracks, is predicted using the area, height, infiltration rate, and heat capacity of a zone. Zone level has heating and cooling load models which use area, internal heat gain, operating hours, heat capacity, and heat flows as input. The energy demand model utilises predictions from zone load models, boiler efficiency, and the coefficients of performance (COP). Each ML component is trained as a separate ML model using the simulation data.

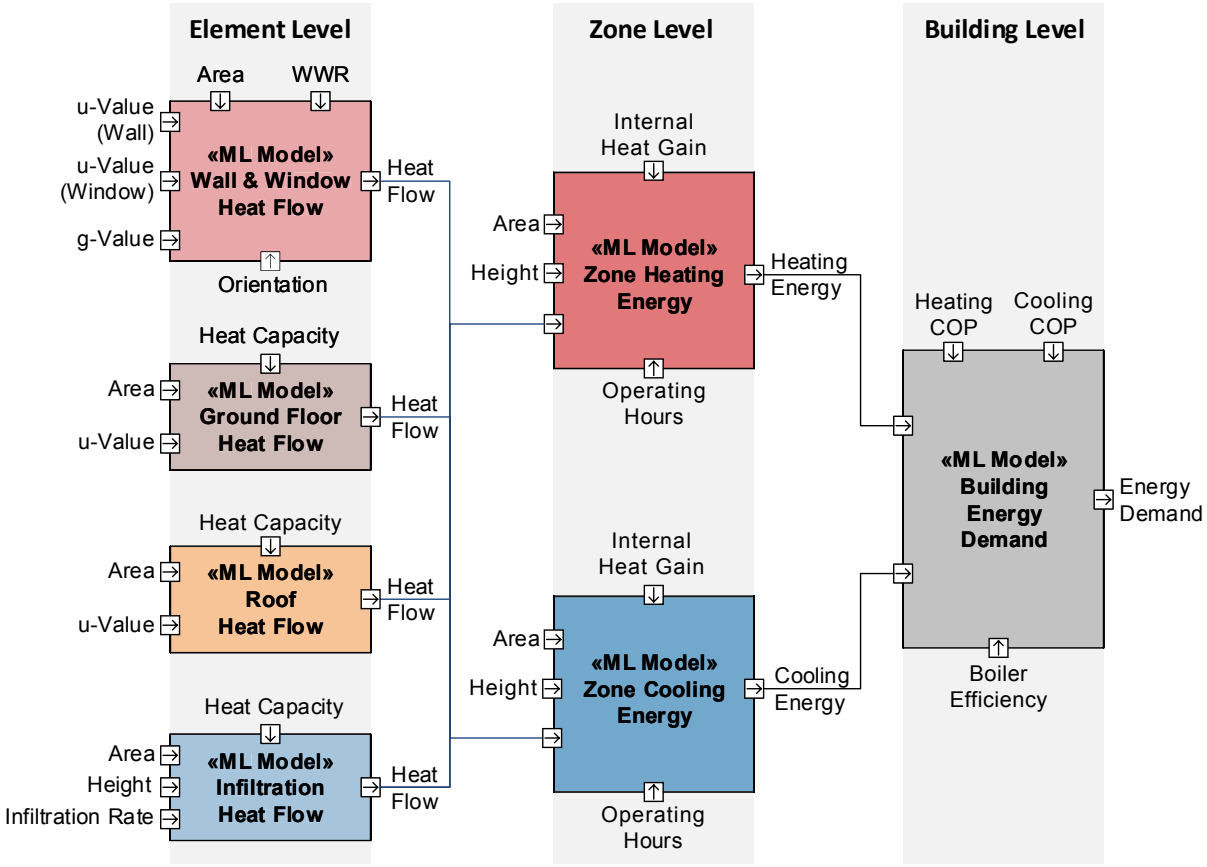

Figure 3.7 Structure of component based machine learning model

Architecture of ML components and hyperparameters

The proposed CBML structure has seven ML components, representing the energy performance of individual building elements. Each ML component has a simple neural network architecture with one input, one hidden, and one output layer. We used the Keras library with the TensorFlow backend for training ML components [130]. L2-regularisation [131] and early stopping [132] are used to restrict overfitting. After a few trials, the learning rate is fixed to 0.001, activation function as a rectified linear unit, and the batch size to one-tenth of data. We tried three different values for the number of neurons in the hidden layer and the coefficient of regularisation for hyperparameter tuning. The values for the hyperparameters are mentioned in

Table 3.3. A total of nine combinations of hyperparameters have been tried, and the combination that has the least validation error is used for further research.

Table 3.3 Values of hyperparameters

Hyperparameter	Values
Number of neurons	25, 50, 100
Regularisation coefficient	1×10^{-3}, 3×10^{-3}, 1×10^{-4}

3 Results

The findings are presented in three subsections. The first subsection describes the changes in the distribution with data increment and enrichment. Subsection 3.2 documents the ML model generalisation changes with each increment and enrichment using scatter plots, error histograms, and numerical error measures. Subsection 3.3 compares the time required to collect data and train the ML model on various training datasets.

3.1 Changes in the distributions of the training samples

The subsection analyses distribution of training samples from the base case, increased, and enriched datasets. After using PCA for dimensionality reduction, the first two principal components capture around 50% of the variance. The principal components are calculated based on 200 test samples representing the design space. The training and test datasets are transformed using these principal components. Figure 3.8 and Figure 3.9 represents the distribution of samples in the design space for increased and enriched datasets, respectively. Both the figures use the same scale for the principal components to allow comparing the distribution of increased and enriched samples. Test samples (grey cross) are overlaid to visualise the variability of building shapes in the design space. It shows that test samples are spread all over the design space, signifying that there are many different shapes in the test dataset. Figure 3.8 shows that the samples from increased datasets are concentrated in one region. It suggests that these samples are similar to each other. It must be noted that the samples have rectangular building shape, but their dimensions and orientations are different. Hence, the samples are slightly different from each other based on the shape.

In contrast, the enriched datasets have samples of four different shapes. Hence, these samples are dispersed away from each other, as shown in Figure 3.9. Moreover, it can be noticed that the samples are of one shape are clustered in one region. The value of mSDD increases from 179 for the base case to 710 for the increased dataset (I-3), while it increases to 891 for the enriched dataset (E-3). Differences in mSDD values for training datasets conclude that enriched datasets have more well-distributed samples than the increased datasets. Hence, to improve ML model generalisation, the aim is to collect samples that increases the mSDD values more than others.

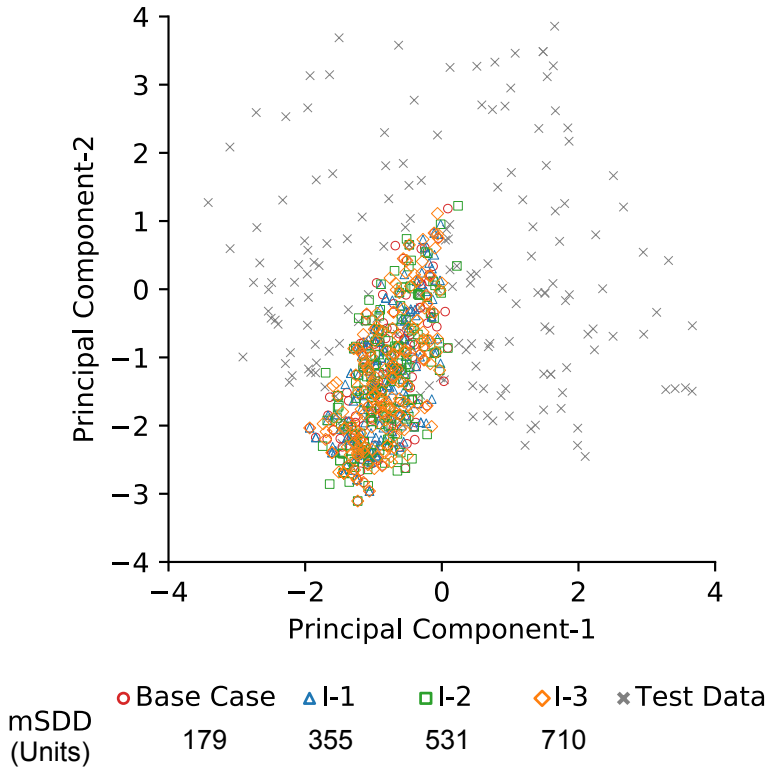

Figure 3.8 Distribution of training samples in the increased datasets

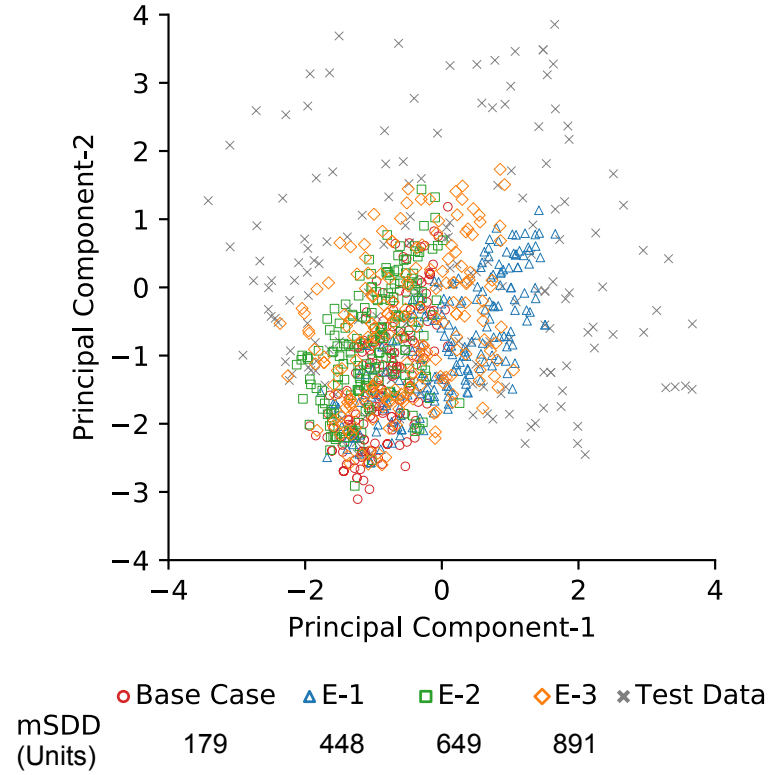

Figure 3.9 Distribution of training samples in the enriched datasets

3.2 Change in the ML model generalisation using increased and enriched datasets

All seven ML components are trained, separately, on each training dataset and the generalisation error is calculated on the test dataset. Three measures, RMSE, R^2, and MAPE, express the generalisation errors in predicted energy demand, numerically, as shown in Table 3.4. Scatter plots and error histograms are used to visualise the error for individual test samples. Figure 3.10, Figure 3.11, and Figure 3.12 show the errors in energy predictions for the base case, increased, and enriched dataset, respectively. The black dashed line in the scatter plots represents an ideal case of making perfect predictions. Hence, test samples with a low prediction error lie close to this line. The error histogram shows the frequency of test samples in a specific range of error. A well-generalising model is characterised by the bars close to 0% error. The box-shaped test samples and other shapes are differentiated in both scatter plots and error histograms. The simulated energy demand of other shapes is slightly higher than box-shaped samples. A primary reason is increased surface area that causes more losses through conduction and infiltration.

Table 3.4 Changes in the generalisation errors with increment and enrichment

	Data Increment			Data Enrichment		
	RMSE (MWh/a)	**R^2**	**MAPE (%)**	**RMSE (MWh/a)**	**R^2**	**MAPE (%)**
Base Case	19.97	0.18	16.3	19.97	0.18	16.3
400 samples	14.18	0.59	11.9	10.96	0.75	9.0
600 samples	13.24	0.64	11.3	9.86	0.80	8.5
800 samples	12.47	0.68	10.7	8.79	0.84	7.7

The generalisation error of the ML model trained on the base case dataset are shown in Figure 3.10. The scatter plot and histogram show that the ML model underpredicts the energy demand for many test samples. The model trained on this dataset has a large RMSE of 19.97 MWh/a, MAPE of 16.3%, and low R^2 of 0.18. Around 50% of test samples have an error of more than ±15%. The box-shaped samples have slightly more accurate predictions than other shapes, as the box-shaped samples are close to the black dashed line and many box-shaped samples are in the range of ±10%.

Figure 3.11 shows that the generalisation errors for the model trained on increased datasets are reducing gradually. Training ML model on bigger datasets improves its ability to generalise. The points in the scatter plots are getting close to the black dashed line by increasing training samples. This observation is correct for both box-shaped and other shapes of test samples. For the ML model trained on the increased dataset (I-3), RMSE reduces around 38% to 12.47 MWh/a, and R^2 increases to 0.68 from the base case. The number of test samples with a higher prediction error reduces also, and MAPE reduces to 10.7% after the increment. The model corrects the underprediction of energy demand as there are more training samples. However, the improvement is relatively small beyond 400 samples.

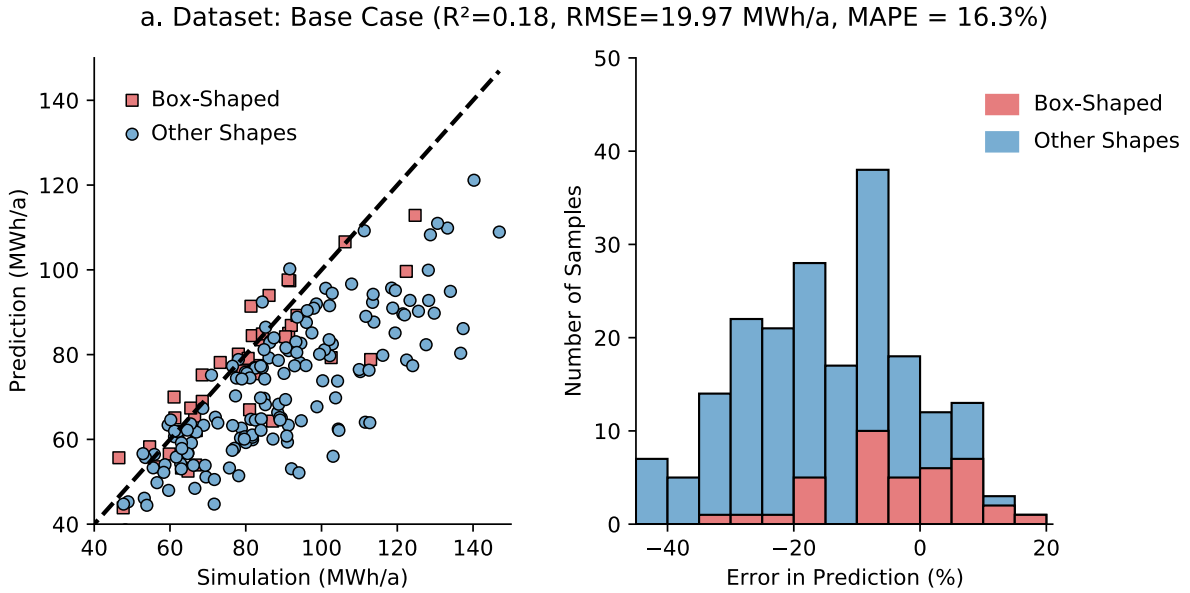

Figure 3.10 Scatter plot and error histogram – ML model training on the base case dataset

Figure 3.12 shows that there is a higher reduction in errors after data enrichment than increment. The ML model corrects most of the underpredictions, and the model trained on the E-3 dataset has more balanced predictions than other training datasets. For enriched dataset E-3, points on the scatter plots are relatively close to the black dashed line, and RMSE reduces around 56% from the base case to 8.85 MWh/a, and R^2 increases to 0.84. The histograms suggest the number of samples with high prediction error reduces sharply with each enrichment step. With data enrichment, the ML model has a higher prediction accuracy for both box-shaped and other shapes of test samples. This observation is evident through scatter plots and histograms as points get close to the black dashed line and bars get close to 0% error. Overall, MAPE reduces to 7.7% after the enrichment (E-3), compared to 10.7% for the increment (I-3).

The difference between the generalisation after increment and enrichment is assessed by comparing plots of Figure 3.11 and Figure 3.12. The numerical error measures for each increment and enrichment step are summarised in Table 3.4.

The scatter plots and error histograms show that the ML models trained on the enriched datasets have lower generalisation errors than the models trained on the increased dataset of the same size. This observation is well supported by a higher reduction in RMSE and MAPE and an increase in R^2 for the enriched dataset than the increased datasets. Around 25 samples out of 200 have an error of more than ±20% for the model trained on the I-3 dataset. However, the number of such samples is only 7 for the model trained on the E-3 dataset. As many as 145 predictions have an error of less than ±10% using the ML model trained on the E-3 datasets; similar predictions are around 100 for the model trained on the I-3 dataset. There are 85 predictions with less than ±5% error for the E-3 dataset and only 55 such predictions for the I-3 dataset.

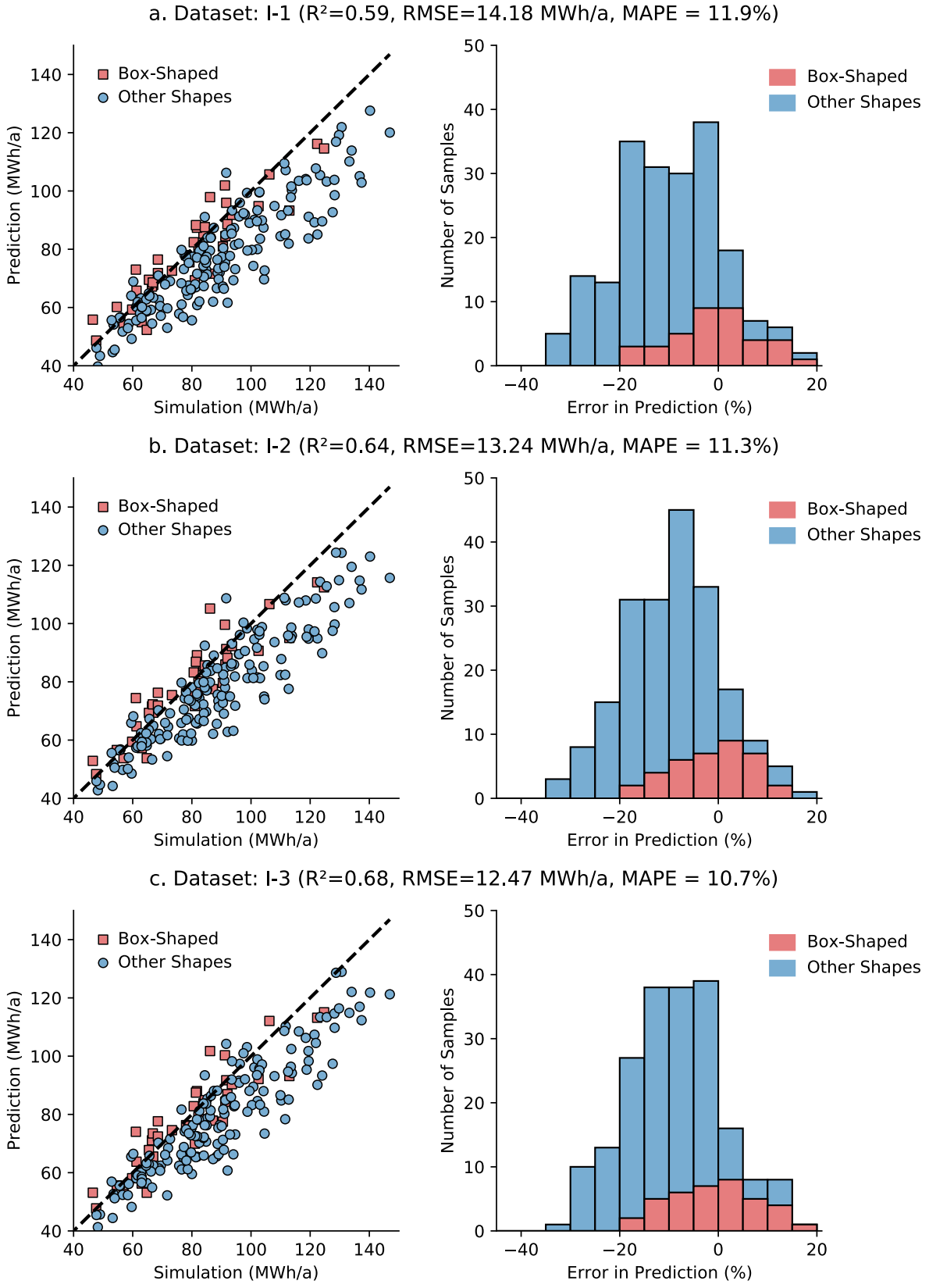

Figure 3.11 Scatter plot and error histogram - ML model trained on increased datasets

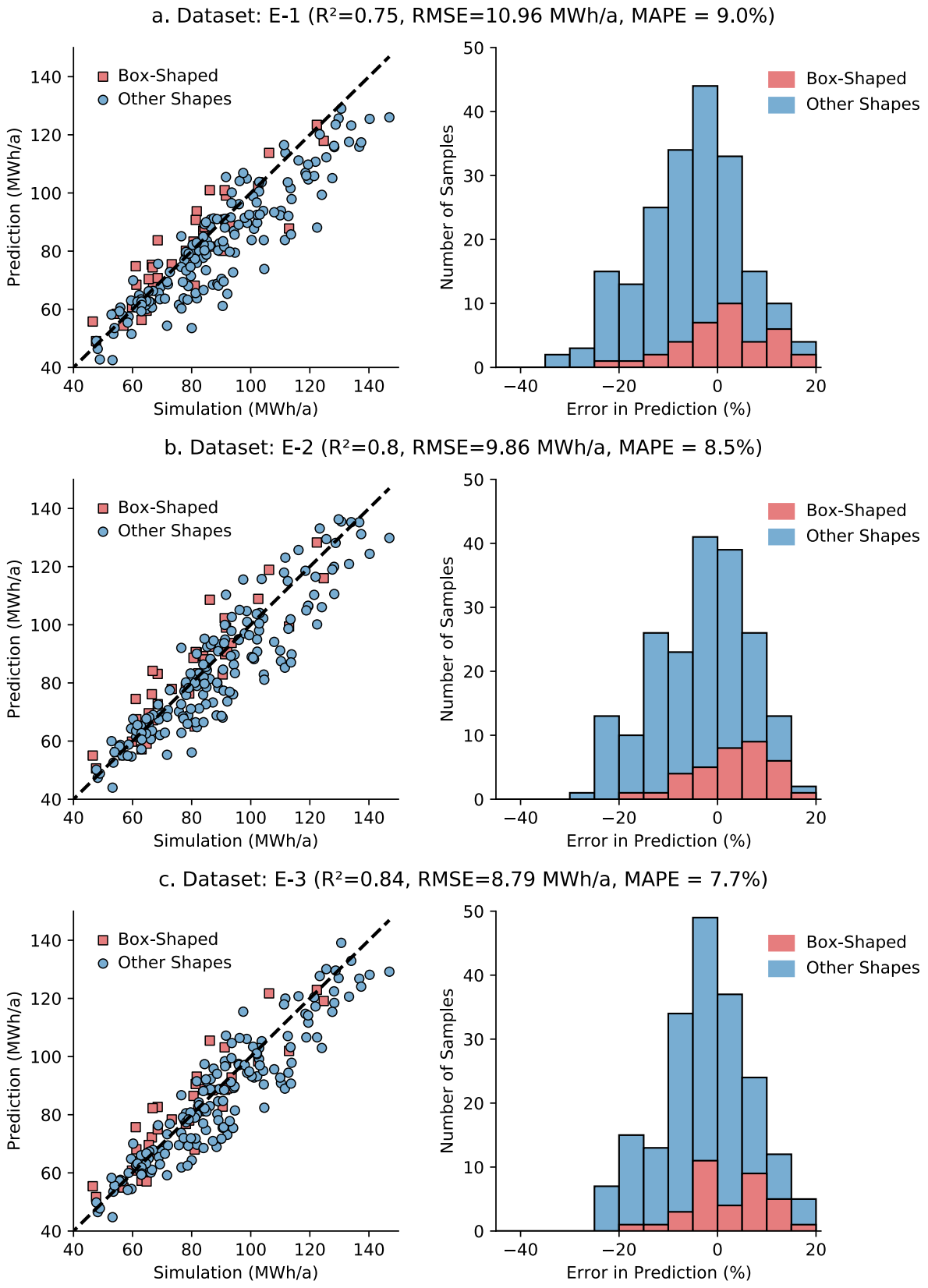

Figure 3.12 Scatter plot and error histogram - ML model trained on enriched datasets

The value of mSDD quantifies the distribution of training samples in the design space. Figure 3.13 shows the value of mSDD for the increased and enriched datasets and the corresponding reduction in the generalisation error - RMSE. The value of mSDD increases for larger datasets as the value of m (the number of samples) increases. However, this value increases more for the enriched datasets than increased datasets. A higher increase in mSDD for the enriched datasets results in a lower generalisation error than the increased datasets, as evident from the figure. The figure shows training dataset with a value of mSDD as 179 units has the model has an R^2 of 0.18. By data increment mSDD increases to 710 units increasing the model has an R^2 to 0.68. The enrichment approach increases mSDD to 891 units that increase the model's R^2 to 0.84.

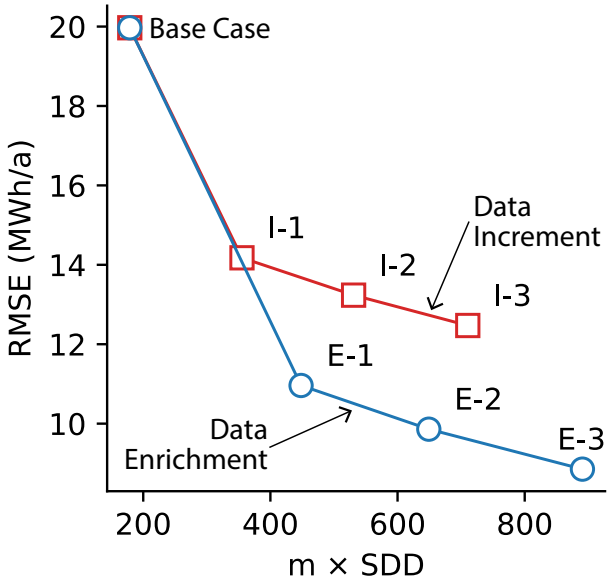

Figure 3.13 mSDD of training datasets and the generalisation errors

3.3 Time required to collect data, train ML model, and make predictions

Collecting samples and training ML models on large datasets requires additional time. Hence, it is important to compare the data collection approaches based on time. The article used a 16-core CPU with a clock speed of 2.4 GHz to report the time. Table 3.5 presents the time required to collect samples and training the ML components. The time reported to collect samples includes time to generate samples, simulate EnergyPlus models, and extract data from output files. Usually, the training time ranges from 18-24 minutes depending on the size of the training dataset, including hyperparameter tuning. It varies only a little across different datasets. However, the time required to collect training samples increases significantly with the size of training datasets. It requires around 10.5 minutes to collect 200 samples of Shape 1. The BEMs of complex shapes, Shape 2 to 4 requires slightly higher time; for example, 200 samples of Shape 2 require 12.5 minutes. Both I-3 and E-3 datasets use 800 samples; but I-3 requires

around 63 minutes while E-3 requires around 86 minutes, including the training time. The prediction time is the same for all the ML models, irrespective of the size of training dataset. It requires 3075 second to simulate the energy use of 1000 samples using dynamic simulations on multi-core CPU. However, predicting energy use using the pre-trained ML model takes only 49.25 seconds. Thus, the pre-trained ML model reduces the prediction time to 1.6% at a loss of accuracy.

Table 3.5 Data collection and training time (in minutes)

	Data Increment		Data Enrichment	
	Data Collection	**Training Time**	**Data Collection**	**Training Time**
Base Case	10.5	18.4	10.5	18.4
400 samples	20.9	21.2	23.0	20.0
600 samples	31.4	21.1	38.3	22.5
800 samples	42.0	21.0	62.0	24.1

4 Discussion

By comparing the two data collection approaches in the early stage BEM context, the article highlights the importance of dispersed training samples to improve the generalisation. The increment approach collects new samples similar to the existing samples. In contrast, the enrichment approach collects samples that are significantly different from the existing samples. Moreover, the article develops a method to quantify the diversity of samples based on a non-parametric characteristic, building shape. The distribution plot shows while the samples in the increased datasets are located close to each other, enriched datasets have training samples that are well-distributed in the design space. A better distribution of samples allows training better generalising ML components and reduces the generalisation errors for enriched datasets than increased datasets.

Previous studies suggest bigger size training datasets allow training better generalising ML models. Since collecting new examples is a resource-intensive exercise, it requires to collect diverse samples to improve generalisation with a limited number of samples. However, it is difficult to identify diverse samples or quantify diversity based on non-parametric characteristics, such as building shape. Hence, the article develops a method to identify dissimilar samples based on the building shape. Using principal component analysis of image, the article proposes the approach to analyse prospective training samples before embarking on data collection exercise. The article develops data collection approaches and analyses new samples for their dispersion in the design space. The ability of various approaches to reduce the generalisation error is assessed by distribution analysis. Further, it uses mSDD to quantify the diversity for large datasets.

As shown in the early stage BEM context, both increment and enrichment approaches use the same number of samples to train the ML model. Compared to new samples of increased datasets

that keep filling the same region, already filled by the existing samples, new samples of enrichment datasets fill the vacant regions of the design space. We found that new samples of increased datasets are close to the existing samples of the base case dataset, which led to an increase in the dispersion (mSDD) to 710 from 179. However, different shaped BEMs of the data enrichment approach led to more dispersed samples and increases the mSDD value to 891. The enriched datasets with well-dispersed training samples capture the characteristics of the test samples that result in lower generalisation errors than the increased datasets. The increased and enriched datasets differ only based on the building shape of samples. Both increased and enriched datasets, after three data collection steps, have 800 samples. The enrichment approach represents an efficient strategy that collects diverse training samples and has a higher potential to reduce generalisation errors. With the same number of training samples, the generalisation errors are lower for the enriched datasets.

The reduction in RMSE is significant after the first increment, given that the training dataset has only 400 samples. The reduction in RMSE is 29% using 400 samples compared to 38% using 800 training samples for increased datasets. The observation suggests that collecting sufficient samples from the box-shaped BEM will improve the generalisation in the beginning. However, once there are sufficient box-shaped samples, the generalisation errors do not reduce much. In this scenario, training samples that have different characteristics than the existing samples should be collected. In the early stage BEM context, it means using BEMs of other shapes than a box. In other data-driven ML applications, it means collecting samples from diverse data sources. Samples from a new source needs to be analysed to ensure that new samples are different from the existing samples and fill the design space. The dispersion of samples in a training dataset may be quantified using standard distance deviation to ensure its ability to train a better generalising model. The distribution of the existing samples can also be used to identify the characteristics of new samples to be collected.

It is interesting to note that the training samples of enriched datasets do not completely fill the design space. It is a possible to reduce generalisation errors further by collecting training samples from more diverse shaped BEMs. However, the article is limited to identifying an efficient data collection strategy to reduce the generalisation error with a limited number of samples. The article develops a method to identify training datasets using distribution analysis that has a higher potential to improve generalisation. It collects new training samples in three increment and enrichment steps to prove that the enriched datasets contain samples that are more diverse and fill the design space better than the increment approach, leading to a lower generalisation error. The model trained on enriched datasets shows an error of 7.7% (MAPE) and 8.79 MWh/a (RMSE). However, there is a question of whether this trained model is suitable to replace dynamic simulations at the early stages without affecting the decision-making. An answer to this question cannot be provided within the scope of this article. Chapter 5 performs further research to answer the question about the suitability of ML models for the early stage energy predictions. There are a few research works that compare the effect of ML model

accuracy on decision-making [13,31,103]. Moreover, the desired accuracy of an ML model depends on its purpose.

The article used a component based machine learning approach to develop an ML model for the early stage BEM, which has seven ML components arranged in a hierarchical structure to predict the energy use. With this approach, we used the ML components trained on simpler design cases to predict the energy use for more complex design cases or the cases which were not present in the training datasets. It shows the benefit of being applicable to design cases that are unknown when training ML components as long as their representation is possible through the model structure. Moreover, only a limited number of design cases are required to train ML components. As in this article, only four different shaped BEMs are used to train ML components, and the test dataset contains many more shapes. Initially, these shapes are selected on the architectural understanding. The training samples are analysed based on their shapes to check which of these samples are different from the existing samples. Once, it is found that enriched samples are significantly different from the existing samples, it is used as a preferred approach to collect samples in the early stage BEM context.

The article developed the ML based energy prediction model for different building shapes but for a fixed location and building use. The article presents a proof of concept of how identifying an efficient data collection approach saves efforts required for data collection that can be extended to other ML applications. For example, to develop an ML model for multiple locations, data enrichment will require collecting new samples from locations characterised by different climates. The generalisation of trained ML models must be interpreted within the context of training and test dataset. Hence, the ML model trained in the article can only be used to predict the energy performance of buildings with use as office, located in Munich, and parameter ranges, as mentioned in Table 3.1. Any deviation will require collecting new training and test samples and retrainig the ML model.

5 Conclusions

Designing energy-efficient buildings requires quickly predicting probabilistic energy use at the early stages. Thus, computationally intensive dynamic simulations need substitution by time-efficient machine learning model, which generalises for various design configurations, including multiple shapes and an acceptable range of technical specifications. The article develops an efficient data collection approach to improve the model generalisation for the early stage energy predictions. After comparing two approaches to collect new samples, the article finds that training samples that are significantly different from existing samples and fill the design space have a higher potential to improve the generalisation than others. The distribution of existing samples should be analysed to identify the characteristics of new samples before embarking on the data collection exercise. Using principal component analysis, the method can be developed to analyse dissimilarity among samples based on non-parametric characteristics. The objective of collecting new samples should be to improve the dispersion of training samples

that capture parameter interactions. New samples, similar to the existing training samples, have only little potential to improve the model generalisation. A similar study needs to be carried out to improve the generalisation of the ML model for various building uses, climate types, and building systems in future. The article also paves the way for developing an efficient data collection approach for other ML models that involves non-parametric characteristics such as shape. A similar approach of defining a design space, analysing the distribution of existing samples to find vacant spots, and collecting diverse data samples that fill the vacant spots is expected to have a similar effect on the generalisation. It will allow focussing on samples relevant to improving the ML model generalisation and saving expensive data collection resources.

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Data availability
The datasets related to this article are available on Mendeley Data [133].

************ (end of the published article) ************

Annexure B. Annexure to Chapter 3

The annexure discusses the findings of the published article in the context of the doctoral research. The objective of the chapter was:

- To develop well-generalising ML models for early stage building energy predictions.

The chapter achieves the above objective by answering - what is the effect of different training samples on the model generalisation? While it is easy to identify and collect well-dispersed samples based on numerical parameters, analysing samples based non-parametric features such as building shape is a complex task. The chapter used principal component analysis to analyse samples' distribution based on their shapes (images). The training samples of the increased and enriched datasets are analysed by visualising their dispersion in the test space. Besides visualisation, a better distribution is also quantified by standard distance deviation (mSDD). A higher value of mSDD indicates that the samples are well-distributed. The analysis concludes that samples of the enriched datasets are more distributed (diverse) and better cover the test space than samples of the increased datasets. The findings reveal that the model trained on enriched datasets have lower generalisation errors than models trained on increased datasets. For 800 samples, the accuracy of the ML model (R^2) is 0.68 for data increment, compared to 0.84 for data enrichment. Thus, well-distributed (diverse) samples, characterised by a higher mSDD, have a higher potential to reduce the generalisation errors than similar training samples.

The developed ML model shows the accuracy of 0.84 (R^2) and the error of 8.79 MWh/a (root-mean-square-error) with the prediction time of 49.25 seconds, compared to the dynamic simulation time of 3075 seconds for 1000 random samples. The chapter proposes a method to improve the generalisation by efficiently collecting new training samples; however, it does not test whether the prediction time and accuracy of the ML model are sufficient for early design stages. Chapter 5 performs detailed research on the suitability of ML models to replace dynamic simulations at the early stages. It is appropriate to consider the following limitations while generalising the results in a broader context:

1. The data collection approaches are used for developing the CBML model for early stage energy predictions. However, these approaches are independent of the ML model structure. Hence, similar approaches to data collection can be used for other ML structures.
2. Since the doctoral research focuses on the early stages and, more specifically, evolving building geometry, the enrichment approach is assumed to collect samples of diverse building shapes. A similar approach can be used to collect samples for many locations where the enrichment will focus on collecting samples from different climates.
3. The chapter includes most early design cases and shape variations; however, the training and test datasets do not include a few building features. Some of these geometric features are pitched roofs, internal courtyards, and non-rectilinear floor plans. However, these features can be included by collecting relevant data and retraining ML models.

4. The chapter considered variations in the building shape and relevant numerical parameters of the early stage design configurations. However, there are a few more design strategies that are considered at the early stages such as shading on windows, flexible shading, night ventilation, and automated lighting control. While the CBML approach is robust enough to capture the effect of shading or natural ventilation from the data, it requires building data with and without these strategies. For example, the data used for training has the building samples that uses natural ventilation, as described in Appendix A; however, it does not have building samples that do not use natural ventilation. Hence, the ML models predict the energy use considering natural ventilation; but cannot predict the energy use when there is no natural ventilation. It requires relevant training data to capture the effect of such design strategies in the ML model and make predictions. In CBML approach, it is possible to train individual ML components to represent the effect of a new strategy.

Conclusions with respect to the doctoral research objectives

The doctoral thesis focuses on providing quick design support by providing energy performance information. The chapter contributes to this objective by improving the generalisation of the early stage ML based quick energy prediction model. The developed model takes around 10 seconds to make probabilistic predictions using 200 samples with an accuracy of 0.84 (R^2). The aptness of the developed ML models for early stage decision-making is the topic of further research (Chapter 5). The chapter improves the ML model generalisation by collecting new samples. It developed an efficient method to collect samples for large datasets. It concluded that a data collection approach, focused on diverse training samples, is more beneficial to improve the model generalisation with a limited number of samples. Data analysis methods such as principal component analysis can be used to assess the diversity of training samples based on non-parametric characteristics. The diverse samples cover the design space that allows training ML models with lower generalisation errors than similar training samples.

4

CNN for early stage ML based energy prediction model

Chapter 4.
CNN for early stage ML based energy prediction model *

General introduction

The chapter focusses on developing machine learning (ML) model for early stage energy predictions. It proposes a new ML model structure to learn building shape characteristics from images and compares it with the previous approaches to answer the following questions:

? Which ML model captures the building shape information better than parametric approaches?

The building geometry makes it challenging to develop ML models for early stage energy predictions. The ML model needs to learn the effect of building shape on its energy demand. Previously, researchers have used parametric representations, shape factor and relative compactness, to capture the effect of shape on the energy predictions. However, building geometry is a complex characteristic to be captured by simple parametric representations.

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* The chapter has been presented in Building Simulations 2021 conference as the following article:

M.M. Singh, P. Geyer, CNN based Quick Energy Prediction Model using Image Analysis for Shape Information, Building Simulations, Bruges, Belgium, 2021.
https://www.researchgate.net/publication/354420055

The general introduction and annexure were not part of the published article and have been added to align its findings with the doctoral research objectives. Minor corrections have been made to the published article to address comments of the PhD committee.

The doctoral researcher has conceptualised, developed methodology and software tools, conducted formal analysis and investigation, visualised the results, and written original draft and made revisions. The last author has helped in writing and revising the article.

Hence, the chapter uses a convolutional neural network (CNN) to learn the building shape feature. A two-dimensional image of the building footprint is used to represent its shape. The output of the CNN model is merged with other numerical design parameters (refer to Figure 4.2). The merged output is fed to a fully connected neural network to make predictions. The generalisation errors of a deep learning model using parametric shape representation and the new ML model using shape representation by an image are compared. It helps to understand whether the new ML model captures the building shape features and its effect on the energy use better than the simpler parametric representations.

CNN based Quick Energy Prediction Model using Image Analysis for Shape Information

Abstract: Data-driven approaches are useful to substitute computationally expensive tools used for energy prediction. These approaches allow developing quick energy prediction models, essential to promote energy analysis at the early stages. However, developing a well-generalising model is challenging due to varying building shape. The article develops such a model using a deep learning approach. A convolutional neural network (CNN) with modified architecture is used to learn from shape and technical specifications. The model predicts energy use intensity with a mean-absolute-percentage-error of 1.51% and root-mean-square-error of 1.06 kWh/m^{2}a. The pre-trained model can predict probabilistic energy performance of 5000 samples in 65 seconds to support informed decision-making under uncertain scenario.

Key Innovations:

- Building shape (image) information is used to train a quick energy prediction model.
- CNN captures the building shape information from an image.
- CNN model is adapted to capture relevant numerical parameters along with shape.

Practical Implications: The developed model makes precise energy predictions at the early stages by using the building shape information. The model is suitable for performing probabilistic energy predictions under uncertain scenarios of the early stages.

1. Introduction

Early design stages are characterised by uncertain design parameters. Hence, activities related to energy-efficient building design such as energy prediction, sensitivity analysis, design space exploration, or optimisation requires building performance simulation (BPS) of several combinations of design parameters [134,135]. However, state-of-the-art dynamic simulation tools used for BPS during the design stage are computationally expensive, rendering them inept for the early stages [52]. Researchers have developed metamodeling approaches to overcome computational expensiveness [102]. In this endeavour, machine learning (ML) approaches help to develop a surrogate model for quick energy predictions. Moreover, the deep learning (DL) approaches are more suitable than other ML algorithms to capture complex interactions of the building energy model (BEM) and predict energy performance with considerable reliability [48].

There are a few limitations to the developed DL approaches, so far, to train energy prediction model. One of these limitations is to develop a well-generalising model for multiple building shapes. The generalisation refers to a surrogate model's ability to predict energy performance

for the samples which were not used for training. Other limitations include the parametric representation of the design artefact that reduces their transferability to new design cases [47]. Early design stages deal with developing building mass model which means the building shape and dimensions vary as per the requirements [31]. Even though architects design building form based on several other factors, a well-generalising model is required to predict energy performance of different possible building shapes and dimensions. In absence of the ML model that can predict energy performance of different shapes, the model needs to be retrained every time architects change the building form.

Most ML based energy prediction model is limited to fixed building shapes and dimensions or rectangular building shape of flexible dimensions [94]. Few researchers developed surrogate models for flexible building shapes and dimensions by representing the shape, parametrically. [46] developed a regression model for different building shapes using shape factor as a parameter to represent shape. [64] used relative compactness to capture the shape information. These surrogate modelling approaches used a parametric representation of building geometry to capture shape information. Other approaches to developing surrogate models for the early stages use the decomposition of the BEM. A DL model structure is developed following an engineering based decomposition of BEM [47,94]. However, the model generalisation for the building shapes outside the training data remains a critical challenge that is insufficiently addressed. There are shape-related effects that are not covered well, such as self-shading. Hence, the article uses image of the building footprint to capture its shape information. An approach of convolutional neural network (CNN) to capture the information from an image is helpful in this regard [136]. CNN algorithm is suitable to analyse images by assigning importance to various parts of images [137,138]. However, using CNN to capture building shape information to predict its energy performance has not been explored well. A research used CNN to capture shape information from images to optimise the carbon footprint [139]. The article adapted the model architecture to capture both shape and technical specification information. The proposed model uses the building shape information from two-dimensional images, making it independent of parametric representation of the building geometry.

The article focuses on developing a surrogate model for quick energy prediction at early design stages. Hence, it investigates an approach to develop a DL model which generalises well for various combinations of building shapes and technical specifications. As building shape is considered to influence energy performance, the shape needs to be well represented in the model architecture. Previous approaches, using a parametric representation of building shape, cause a loss of information, limiting the generalisation of a model for new design cases. The article investigates a CNN model architecture to capture the shape information from an image. A parametric DL model is also developed, which uses a parametric representation of building geometry by area-to-volume ratio. The abilities of the DL model and CNN model to generalise are compared to assess the importance of capturing shape information from an image.

2. Research Methodology

The article develops energy prediction models using deep learning approaches. The building characteristics affecting energy performance are broadly classified as building geometry and technical specifications. Hence, the DL models should capture both geometrical and non-geometrical information to predict energy performance. Two model architectures have been compared in the article. The first model is a conventional deep neural network (DNN) that uses a parametric representation of building geometry to capture the shape information. The second model is convolutional neural network (CNN) that uses an image to capture the shape information. By comparing the accuracy of these two models, the importance of capturing the shape information by an image instead of a parameter in developing an energy prediction model is discussed. The section describes the model structures, hyperparameter tuning, and the measures for the generalisation errors. The details of the test case and data collection are also provided.

2.1 Deep neural network (DNN) architecture

Previously, researchers developed monolithic models using conventional DNN. This model architecture has been developed as a base case to understand the model generalisation, which can be achieved using the existing approaches. Conventional DNN model architecture, used in this article, has an input layer, two or three hidden layers, and one output layer, as shown in Figure 4.1. The figure also lists all the design parameters that have been used as input to the model, such as the number of floors, U-values, and infiltration. The building shape is represented by a parameter – area-to-volume ratio.

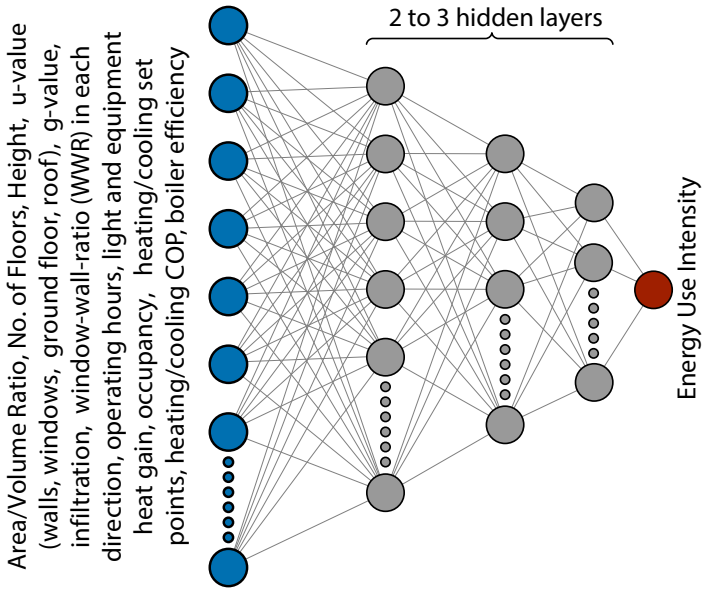

Figure 4.1 Architecture of the DNN model

There are a few hyperparameters that represents the model structure and learning algorithm such as number of neurons, regularisation coefficient, and learning rate. These hyperparameters

are fixed at the beginning of the training the DL model. Hyperparameter tuning refers to finding an appropriate combination of these hyperparameters. We kept 20% of the training samples (validation dataset) for hyperparameter tuning. It is the best practice to try several combinations of hyperparameters and select the best combination based on the least validation error, i.e., the lowest prediction error on the validation dataset. An incorrect selection of hyperparameters will result in underfitting, characterised by a high training and validation error; or overfitting, characterised by a low training error and a high validation error.

In the DNN model, we experimented with the hyperparameters, mentioned in Table 4.1. A total of 16 random combinations of hyperparameters have been tried. The combination of parameters with the least validation error is highlighted in bold in the table. The model having the lowest validation error has been used to report the generalisation errors.

Table 4.1 Values of hyperparameters for DNN model

Hyperparameter	Values
Number of layers	2, **3**
Neurons in layer 1	**40**, 80
Neurons in layer 2	**20**, 40
Neurons in layer 3	5, **10**
Coefficient of regularisation	**1e-06**, 1e-05
Activation function	**Rectified linear unit**
Learning rate	**0.001**

2.2 Convolutional neural network (CNN) architecture

Contrary to a conventional deep neural network, a convolutional neural network (CNN) captures the building shape information from an image. The representation of building shape by an image allows the CNN model to capture sufficient information about the shape and its effect on the energy performance. Other design parameters such as height, infiltration, U-values, and infiltration also affect energy performance. Hence, the article has adapted the CNN model architecture to use both shape information from an image and parametrically represented technical specifications.

The adapted CNN model architecture is described in Figure 4.2. The article assumes that a building has the same floor plan at each level; hence, a floorplan defines the building shape. A grey-scale image of size 50×50×1 is used to represent the shape. The first two dimensions, '50×50', describe the number of pixels in a two-dimensional cartesian plane. Each pixel is equivalent to one meter. The third dimension '1' describes the number of channels. A coloured image has three channels – red, green, and blue while a grey-scale image has only one channel. A pixel has a value between 0 (black) and 1 (white). Black pixels show the building footprint and white pixels show the empty space. As shown in Figure 4.2, the image input is processed through many convolved layers. The input layer connects to one or many convolved layers. A

convolved layer is a two-dimensional layer with its neurons connected to specific regions of the image. Convolved layers are connected to two-dimensional pooled layers. Neurons in a pooled layer take an average of specific neurons of the convolved layer. Finally, two-dimensional pooled layers are flattened into a one-dimensional vector. The one-dimensional vector is considered as the output of the CNN model. Parametrically represented technical specifications, which are also one-dimensional vector, are merged with the output of the CNN model. The merged model has a few fully connected layers to make the energy predictions. More details of CNN terminology can be found in [140].

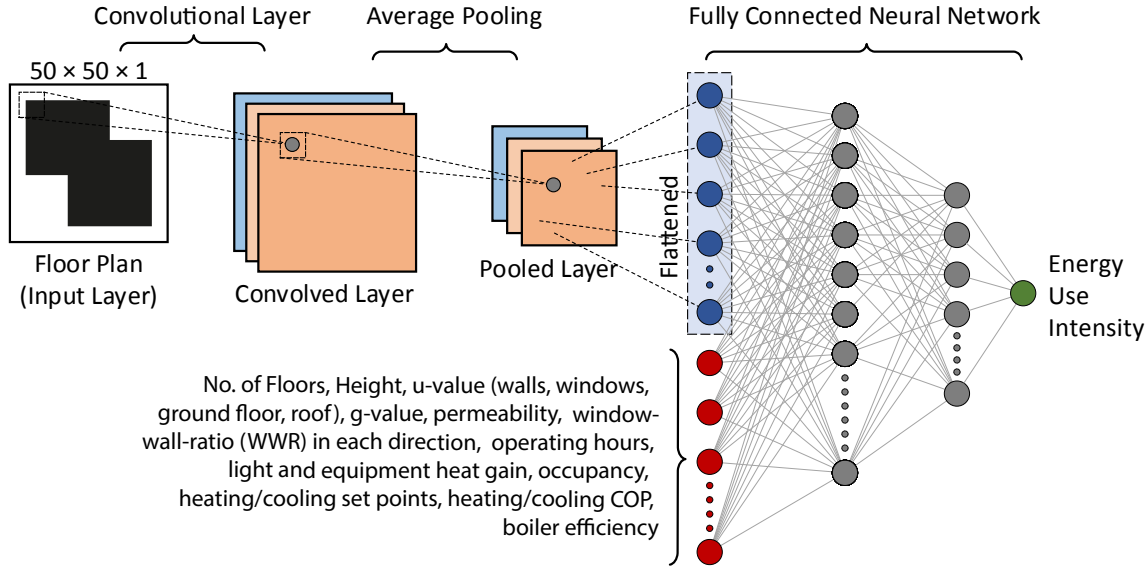

Figure 4.2 C-D-NN model architecture

Figure 4.3 Hyperparameters for C-D-NN model

Hyperparameter	Values
Number of convolution layers	2, **3**
Kernel size	3×3, **5×5**
Stride	**4×4**
Pooling size	**10×10**
Neurons in layer 1	**40**
Neurons in layer 2	**20**, 40
Neurons in layer 3	5, **10**
Coefficient of regularisation	**1e-06**, 1e-05
Activation function	**Rectified linear unit**
Learning rate	**0.001**

There are many hyperparameter in the proposed CNN model. We experimented with the hyperparameters, mentioned in Figure 4.3. As described in the previous subsection, we tested 16 random combinations of hyperparameters. The combination of parameters with the least validation error is highlighted in bold in the table.

2.3 Testcase

The proposed approaches of training the models are tested on a medium-size office building in Munich. The ranges of the design parameters are as mentioned in Table 4.2. The values of these parameters have been selected based on German standards and previous research works [22,103]. The building shapes are randomly generated by arranging squares of different sizes. More details about generating these random shapes have been document in Appendix C. A few of the random shapes are shown in Figure 4.4. Each random shape has different floor area based on the sampled value of 'floor area' parameter.

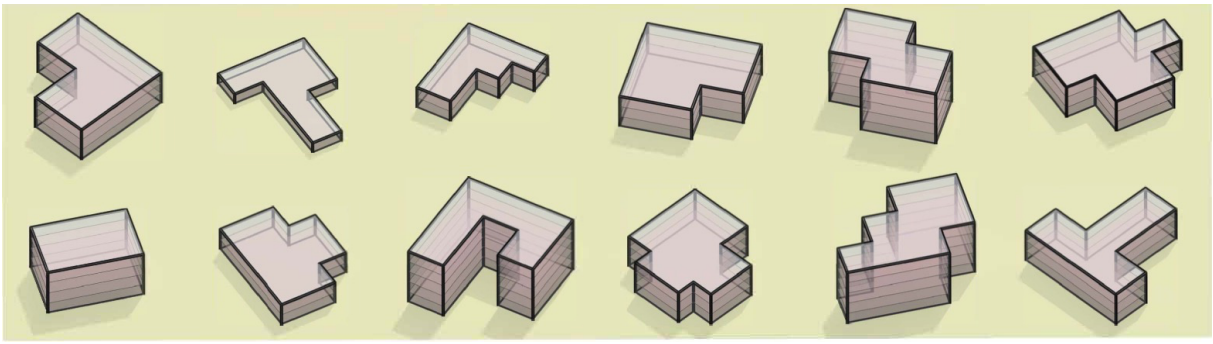

Figure 4.4 Building shapes of training and test example

Table 4.2 Ranges of the design parameters

Parameters	Unit	Min	Max	Parameters	Unit	Min	Max
Floor Area	m^2	800	1600	**Heat Capacity (Slab)**	kJ/m^3K	0.8	1.2
Floor Height	m	3.0	4.0	**$WWR_{N/E/W/S}$**	-	0.2	0.8
No. of Floors	-	3	5	**Internal Mass**	kJ/m^2	60	150
Orientation	°	0	45	**Permeability**	$m^3/h{\cdot}m^2$	4.5	7.5
U-value (Wall)		0.15	0.35	**Operating Hours**	h	8	12
U-value (Ground Floor)		0.15	0.35	**Occupant Load**	m^2/Person	15	20
U-value (Roof)	W/m^2K	0.15	0.35	**Light Heat Load**	W/m^2	4	10
U-value (Window)		0.6	1.0	**Equipment Heat Load**		4	10
U-value (Internal Floor)		0.2	0.5	**Heating COP**		2	5
g-value	-	0.4	0.8	**Cooling COP**	-	2	5
				Boiler Efficiency		0.85	0.95

2.4 Data collection and estimation of model generalisation

It requires a large amount of data to train and test ML models. The article uses the simulation data, generated using EnergyPlus [33]. An EnergyPlus model has been calibrated using the measured energy consumption data. Appendix B provides more details of the developed EnergyPlus model. In the article, the predicted energy account for energy to provide heating, cooling, and lighting. For generating training and test datasets, the parameters mentioned in Table 4.2, are sampled using Sobol [111] and Latin hypercube sampling [110], respectively. An energy model is generated corresponding to each sample. The relevant design parameters

are adjusted, based on the sampled values, to generate samples. Both ML models are trained on 25000 samples. The ability of the models to generalise is estimated by the prediction accuracy on unseen samples; hence, 5000 random test samples, which were never used for training, are used. The generalisation error is calculated using two performance measures, the first-order measure - mean-absolute-percentage error (MAPE) and the second-order measure - root-mean-square-error (RMSE). The two measures are chosen to account for the errors over the entire range of predictions. The article also uses error histogram and scatter plots to visualise the magnitude of errors in individual test samples.

3. Results and discussion

The section compares two DL models, i.e., DNN and CNN model. CNN model is more complex than the DNN model; hence, CNN requires more time to train and make predictions. However, the CNN model is expected to have better generalisation than the DNN model by capturing the shape information, appropriately. The two subsections compare the models based on the generalisation errors and training and prediction time.

3.1 Model generalisation

The model generalisation is estimated using the prediction accuracies of DNN and CNN models for 5000 randomly generated test samples. The numerical performance measures, RMSE and MAPE assess the overall model generalisation. Histograms and scatter plots visualise the prediction errors in individual test samples. We found that the DNN model has an RMSE of 1.27 kWh/m^{2}a and MAPE of 1.82%. The Scatter plot in Figure 4.5 suggests that the DNN model predictions are close to the simulation values. However, a few examples are away from the black-dashed line indicating both under-prediction and over-prediction using this model. The histogram in Figure 4.5 also suggests around only 3200 out of 5000 examples within the error range of ±2%. The remaining examples have a higher error than this value. RMSE and MAPE for the CNN model are 1.06 kWh/m^{2}a and 1.51%, respectively.

Both errors are around 17% less for the CNN model than the DNN model. The decrease in the generalisation errors is well corroborated by the scatter plot and the histogram in Figure 4.6. The comparison of scatter plots shows that the predictions from the CNN model are more accurate than the DNN model. Most of the examples are close to the black-dashed line in the scatter plot. It suggests that the DL model is making the same prediction as the simulation values. Similarly, the histogram suggests more examples with less than ±2% error for the CNN model than the DNN model. Around 3700 out of 5000 samples has an error of less than ±2% error. Only 67 samples have an error of more than 6% for the CNN model while for the DNN model 265 samples have more than 6% error.

3.2 Training and prediction time

The DL models are trained using the deep learning library from TensorFlow. The training and prediction times are reported based on a machine having sixteen CPUs with a clock speed of

2.4 GHz. It has a dedicated GPU, "NVIDIA Quadro M2000". The libraries were optimised to utilise the full computing power. The time for training the DNN model is 691 seconds, including hyperparameter tuning, while this time is 7895 seconds for the CNN model. Hence, the training time is 11 times more for the CNN model compared to the DNN model.

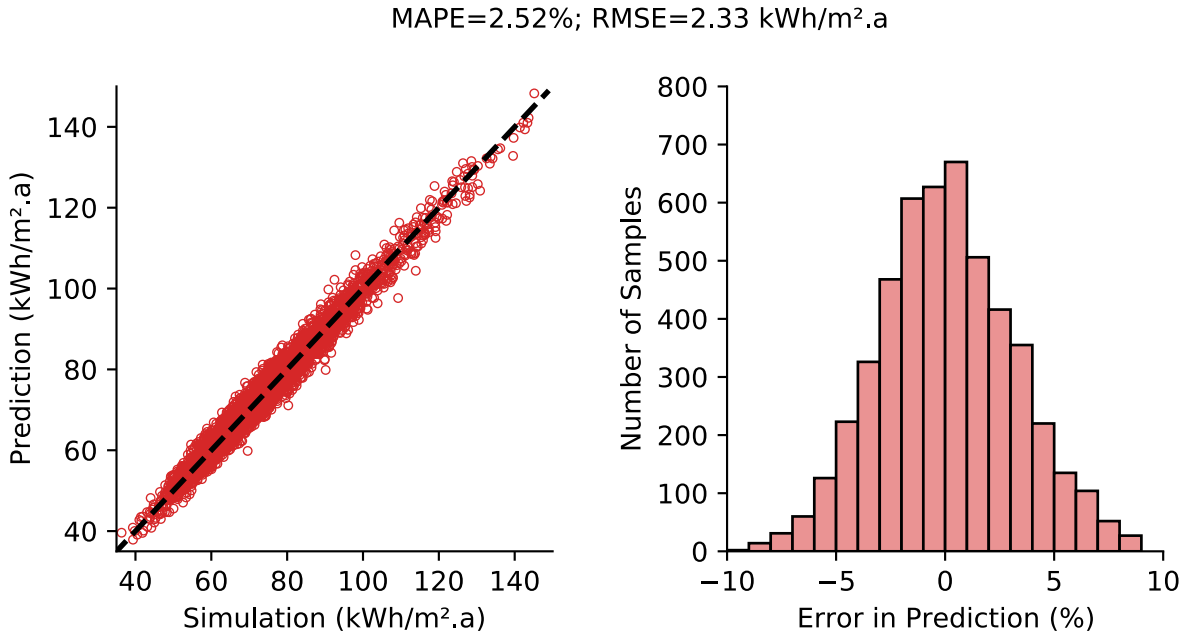

Figure 4.5 Scatter plot and error histogram for DNN model

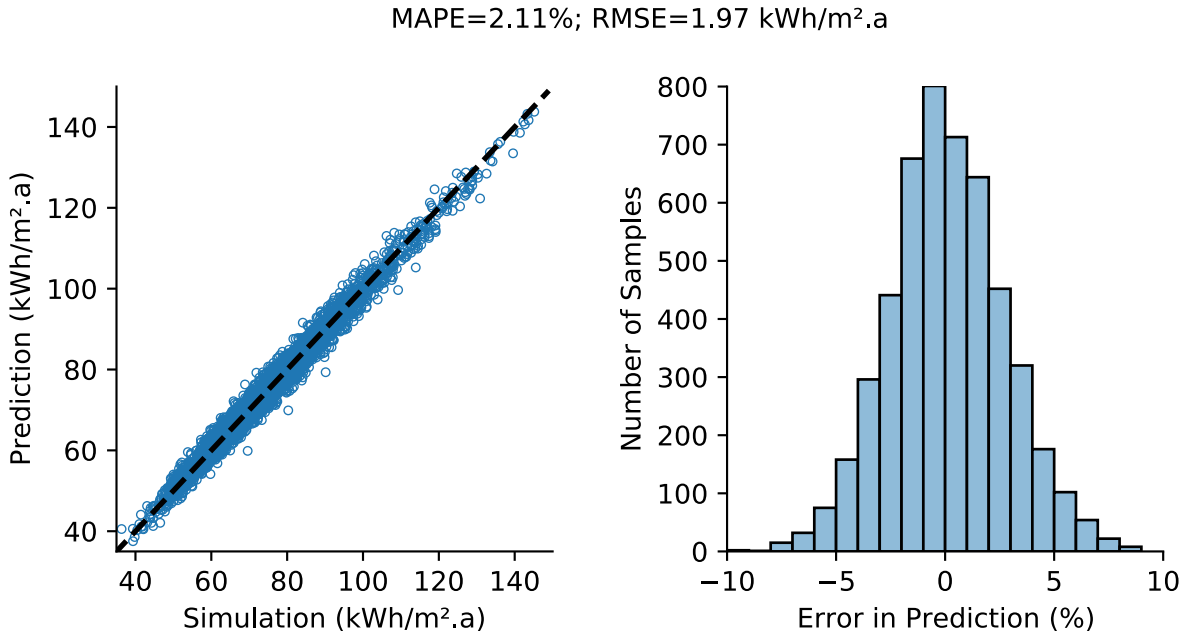

Figure 4.6 Scatter plot and error histogram for CNN model

The researchers also developed a plugin for the building information modelling (BIM) tool Revit. The plugin uses the developed DL models to predict probabilistic energy performance. It is implemented using C# and TensorFlow library in python. It takes around 35 seconds to predict energy prediction for 5000 examples using the DNN model and 62 seconds using the CNN model. The prediction time includes preparing the data from the BIM tool and integrating the energy prediction results into the BIM tool. The prediction time is 77% more for the CNN model compared to the DNN model.

4. Conclusions

The article used deep learning to develop a quick energy prediction model. An adapted model architecture of a convolution neural network is used to capture information about the shape by image analysis. This information, in combination with design parameters, serves to predict the energy use. While a convolutional neural network captures the shape information from an image, a conventional deep neural network captures this information from a parameter. The prediction accuracy of the new model has been compared with the conventional deep neural network to assess the importance of capturing the shape information from an image. The conventional model is treated as a base model. The training and prediction times are more for the proposed model than the base model. However, the new model has a 17% lower generalisation error than the base model. A higher reduction in the generalisation error concludes that the visual representation and shape analysis by a convolutional network are better able to exploit the geometrical information than the parametric approach. The visual representation of building shape helps to capture its effects on the energy predictions better that might be lost in a parametric representation.

Data availability

The data used for training and testing the ML models and the trained ML models are available on Mendeley Data [141].

********** (end of the published article) **********

Annexure C. Annexure to Chapter 4

The annexure discusses the findings of the published article within the doctoral research objectives. The objective of the chapter was:

- To develop well-generalising ML models for early stage building energy predictions.

The chapter achieves this objective by answering which ML model captures the effect of building shape on the energy use – a conventional deep neural network (DNN) that represents the shape by a parameter or convolutional neural network (CNN) that uses image of the building footprint to represent the shape. The chapter adapts the model structure to combines output from the CNN model with other design parameters to make energy predictions. It showed that the new model structure has lower generalisation errors than the conventional DNN or parametric ML model. These findings are used to conclude that by capturing building shape information from an image, the CNN model allows learning the effect of building shape on its energy performance better than the parametric approach; hence, smaller generalisation errors.

The doctoral research primarily focusses on medium-size office buildings in Munich, Germany. However, the developed methods are also valid for other locations. The methods have been tested by developing the ML models for two additional locations – Berlin, Germany and Brussels, Belgium. It also improves the practical application of the ML models. The climate of Brussels and Berlin are classified as Cfb in the Köppen classification system, same as Munich [59]. Since the building typology and climate does not differ much among these locations, the same tools can be used for data collection. It is difficult to test the developed methods for entirely different climate due to practical reasons. First, it will require calibrating EnergyPlus model using the real data. Second, it will require to write a program to automate generating EnergyPlus model.

The annexure develops the ML models for three locations – Munich, Berlin, and Brussels, separately. The training datasets consist of 75000 samples, 25000 samples for each location, and the test datasets consist of 3000 samples, 1000 from each location. The same CNN model structure and hyperparameter tuning is used, as described in the chapter. The accuracy of ML predictions is presented in Figure 4.7 using scatter plot and error histogram. The mean-absolute-percentage-error (MAPE) of 2.02% and root-mean-square-error (RMSE) of 1.66 kWh/m^{2}a suggests that the models generalise well for different locations. Scatter plots also suggest the same, as most of the samples lie close to the black-dashed line that shows as ideal situation of making perfect predictions. The error histogram shows that close 2500 samples out of 3000 samples have an error within the range of ±4%. Moreover, the ML models show same error frequency for all the locations. Thus, it suggests that the methods can be used to develop the ML models for different locations.

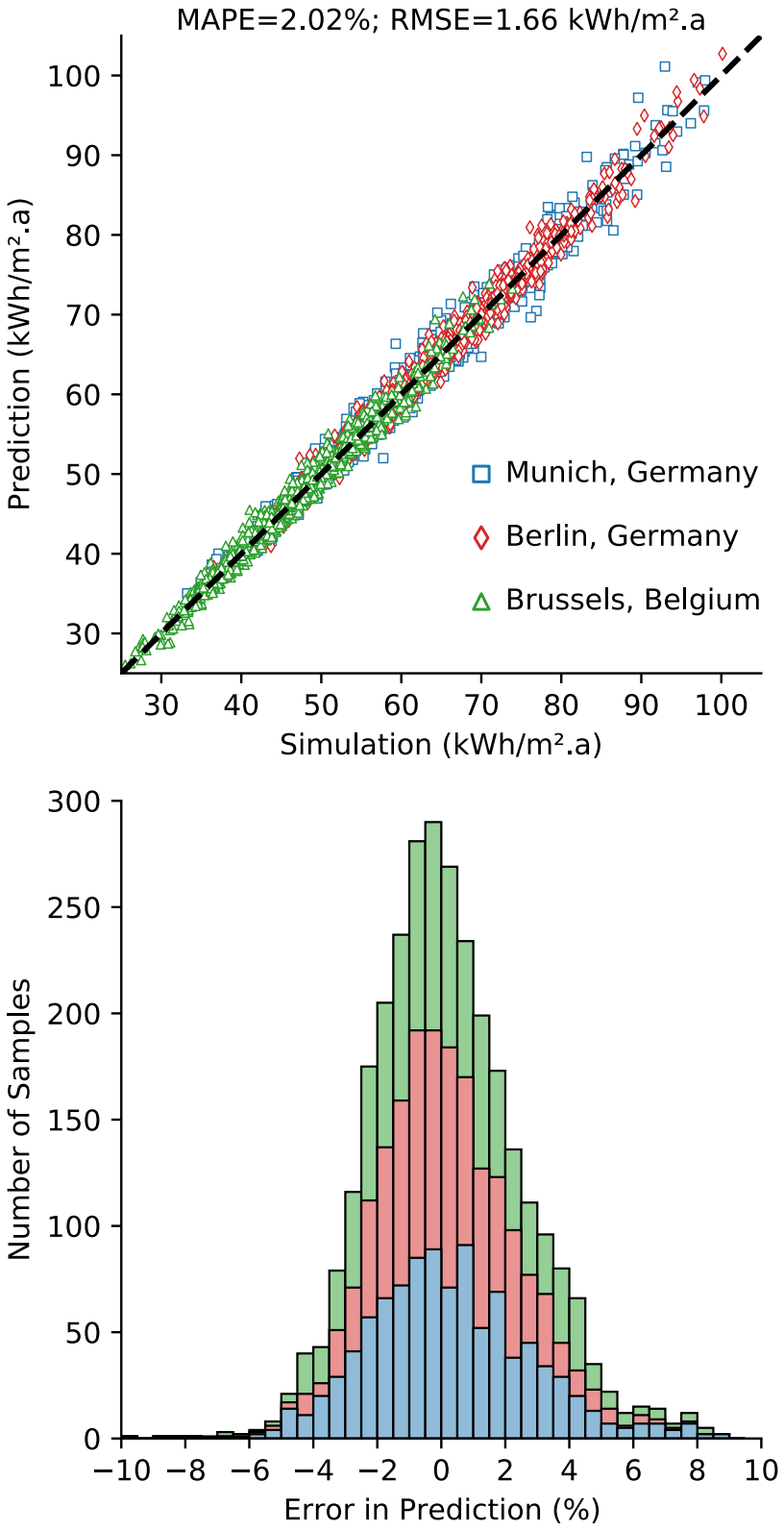

Figure 4.7 Accuracy of ML predictions for Berlin, Brussels, and Munich

The presented approach of the CNN model greatly overcomes the challenge of evolving building geometry at early design stages and contributes to developing a well-generalising ML model for early stage energy predictions. While training and test cases are generated to meet several requirements of early stage design cases, the following limitations must be considered while interpreting these results in a broader context:

1. The chapter assumes that the building shape is represented by its footprint using a two-dimensional image. While this assumption is appropriate for the buildings with the same floor plan at each level, it is incorrect for more complex buildings that have different floor plans at different levels. However, the model can be extended using three-dimensional CNN to capture such complex shapes.
2. The developed ML model structure has been tested for Munich, Berlin, and Brussels; however, these locations come under the same climatic classification. The ML models need to be trained and tested for other locations with different climates for wider applications.
3. The chapter tries to include shape variations of the early stages; however, many building features are not included in the datasets. Some of these prominent characteristics are pitched roofs, internal courtyards, and non-rectilinear floor plans. The ML models can learn these features; however, new data is required to incorporate these features.
4. Early stage design also requires evaluating the effect of design strategies such as night ventilation, movable shadings, or under floor heating on the energy use. The developed ML model cannot be used to evaluate such strategies. It will require collecting new samples to train the ML model. For example, to evaluate the effect of night ventilation, the samples should have both types of buildings - that use night ventilation and that do not use night ventilation. Then, an input parameter needs to be introduced to represent its use. The ML model can be retrained on the new data to predict the energy use of the buildings using and not using such strategies.

Conclusions with respect to the doctoral research objectives

The chapter contributes to the doctoral research objective by developing a machine learning (ML) model that has lower generalisation errors than previously developed approaches. The proposed ML model structure has a convolutional neural network (CNN) to process information from an image that captures the effect of building shape on its energy demand. The output of the CNN is merged with other numerical design parameters and fed to a fully connected network to predict the energy use. The proposed ML model has the root-mean-square error of 1.97 kWh/m^{2}a compared to 2.33 kWh/m^{2}a for the parametric approach. The prediction time is only 62 seconds for 5000 samples which is significantly lower than the dynamic simulations. Since ML models rely on learning from training data, it is mandatory to consider its limitations for practical applications.

5

Quick energy prediction for comparing design options

Chapter 5.
Quick energy prediction for comparing design options *

General introduction

The chapter determines the suitability of machine learning (ML) based quick energy predictions for comparing design options (decision-making) at the early stages. The chapter answers the following question:

? What are the acceptable limits of error (prediction gap) for ML models that do not affect the comparative assessment of design options at the early stages?

The chapter studies the effect of substituting dynamic simulations by ML models on the early stage decision-making. ML models reduce the computational time at the cost of accuracy. Hence, it requires to study whether the reduced accuracy will affect the decision-making or not. In the chapter's context, early stage decision-making refers to comparing design options. A design case of a medium-sized office building is used to study how energy predictions are used

* The chapter is originally published as the following article in a peer-reviewed journal:

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The general introduction and annexure were not part of the published article and have been added to align its findings with the doctoral research objectives. Minor corrections have been made to the published article to address comments of the PhD committee.

The doctoral researcher has conceptualised, developed methodology and software tools, conducted formal analysis and investigation, visualised the results, and written original draft and revisions. The remaining authors have helped in conceptualisation, visualisation of the results, and writing the article.

to compare options at the early stages. Besides ML models, other approaches to reduce the computational time, have also been tested. The chapter assumes that the probabilistic approach to address uncertainty, detailed core-and-perimeter zoning to create zones, and dynamic simulations to predict energy use provides the most accurate results to compare design options. The chapter studies three alternative approaches - deterministic approach to address uncertainty, one-zone-per-floor to create zone, and ML models to predict energy demand. Since the alternative approaches will have some errors, these approaches are examined for their reliability for decision-making. The doctoral research primarily focusses on assessing the suitability of ML models for energy predictions. It is assessed whether the errors in ML predictions are 'small' enough to obtain the same comparison results as the primary approach. The chapter implements the proposed approaches to compare design options using a plugin for the building information modelling (BIM) tool, Autodesk Revit [142]. The BIM tool has been used as a facilitator to create and store design options. It allows using any of the proposed approaches to compare design options. The developed plugin facilitates comparing the proposed approaches based on the modelling and the prediction time and their ability to provide correct comparison results.

Quick energy prediction and comparison of options at the early design stage

Abstract: Energy-efficient building design requires building performance simulation (BPS) to compare multiple design options for their energy performance. However, BPS is often ignored at the early stage due to uncertainty, lack of details, and computational time. The article studies probabilistic and deterministic approaches to treat uncertainty; detailed and simplified zoning for creating zones; and dynamic simulation and machine learning (ML) 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 using an alternative approach, such as an ML model. However, alternative approaches cause prediction gaps that require investigating their effects on comparing options. A plugin for building information modelling (BIM) tool has been developed to perform energy prediction and decision-making 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 use is treated as the reference method. The deterministic or ML approach has a small prediction gap, and the comparison results are the same as the reference method. The simplified model approach has a large prediction gap and makes only 40% comparison results 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

Energy-efficient design is essential for every building project. 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 [143]. Nevertheless, quick evaluation and analysis of the options using a set of established tools provide relevant information for the assessment [97,144]. The concept of performance based design, which got traction in the past few years, is based on computational modelling and simulation to assess design options [145–147]. Since we need to design energy-efficient buildings, effective use of building performance simulation (BPS) results is necessary to assess design options based on their energy performance.

Furthermore, a designer should focus on the energy performance from the early design stage as the early stage decisions improve the performance at a lesser cost of changes [148,149].

However, the energy performance prediction at early stages has several impediments such as expensive modelling efforts, uncertain building characteristics, and high computational time [52,54,135,150]. 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 [151]. Thus, we are developing a building information modelling (BIM) integrated tool to make quick energy predictions and compare options. However, this development requires investigation into various early stage quick 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 [33], TrnSys [35], ESP-r [34], and building library for Modellica [152]. Achieving a high level of accuracy requires a detailed building energy model (BEM), which is computationally expensive. Still, there exists some performance gap between the simulated energy demand and the actual energy consumption due to limitations of the simulation tool [153–157]. Addressing the performance gap is a vast domain of research in itself, and many research works are focussing on validation of simulation tools [158].

Moreover, the design process requires a simulation tool, which provides BPS results exactly when it is required [159,160], i.e. computationally fast enough to fulfil the requirements of the early stages. It requires a simplified energy model to reduce computational time, which causes an additional error, i.e. prediction gap [48]. A ‘large’ prediction gap that can affect the decision-making will render BPS results unreliable. However, a ‘small’ prediction gap with a significant reduction in the computational time will be useful for the early stages. The article focusses on the prediction gap and its effect on comparing design options. It defines the prediction gap is ‘small’ if it does not affect the results to compare design options at the early stages.

At the early stages, BPS results are used for comparing and classifying several options rather than accurately predicting the energy use of one option [31]. It must be noted that achieving a very high level of accuracy is time-consuming and unrealistic, as several details are still developing and many parameters are uncertain [34,161]. However, it is worth investigating how energy prediction approaches can support decision-making under uncertain scenarios of the early stages.

1.2 Uncertainty, energy modelling and high computational time for BPS

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 [162,163]. From an early design perspective, uncertainty caused by scenario and design parameters is more relevant as other uncertainties are related to detailed BEM and precise energy predictions. A usual practice is to predict the energy performance using average values of uncertain parameters and rely on experts to compare design options. However, uncertain

design parameters require a probabilistic approach to predict energy use [28]. The probabilistic approach uses a random sampling of uncertain parameters and predicts the energy demand of a few hundreds of models for one design option [99,163]. A statistical analysis of probabilistic energy predictions is performed to make a comparison under uncertainty [99]. The domain of social and behavioural sciences has widely used statistical tools to ascertain whether the effects of two treatments are different from each other [164]. In analogy to BPS, it is used to determine which one of the two options, has a better energy performance under uncertainty.

Energy modelling is complicated at the early stages as many building details are not developed. Designers develop only the building envelope at the early stage. Thus, the information about thermal zones, required to develop a BEM, is not present in the design model at the early stages. Many researchers developed guidelines to create zones for the early stage designs that do not have zones [165,166]. These guidelines also include approximation of thermal properties of building envelope and assumptions related to building use [167]. However, the selection of a zoning strategy remains an essential aspect of energy modelling at the early stages [168]. There have been a variety of approaches to automatically generate zones such as one-zone-per-floor, perimeter depth zoning, cardinal direction zoning, core-and-perimeter-zoning [169–172]. Among these approaches, ASHRAE's core-and-perimeter-zones approach yields the most reliable results and used widely at the early stages [165,173,174]. However, this approach requires expensive modelling efforts and computational time. In contrast, one-zone-per-floor requires relatively fewer modelling efforts and computational time. However, this approach has a higher prediction gap than core-and-perimeter-zoning [168,175]. While core-and-perimeter-zoning have perimeters zones along each edge and performs detailed calculation of solar heat gains, one-zone-per-floor approach has only one zone receiving solar radiation from every direction throughout the day. It leads to an incorrect estimation of heating, cooling, and lighting loads; hence, one-zone-per-floor approach has a higher prediction gap.

Dynamic energy simulations, which promise an accurate estimation of energy use, require a high computational time. If one simulation is required to assess a design option, it is not computationally intensive and takes around five minutes. However, the probabilistic approach requires a simulation of a few hundreds of models for each design option. It makes dynamic simulations computationally intensive and makes them unfit for the early stage [176]. The need to reduce computational time requires a quick energy prediction model. Simpler methods such as quasi-steady-state method are relatively quick; but, fail to capture the dynamic behaviour of BEM and have large prediction gaps [177,178]. These simpler methods require calibration for a specific building case [179–181]; hence, it is not possible to use these approaches in this article. Researchers have proposed data-driven approaches when a task requires predicting energy demand of several thousand design combinations [38,39,47]. 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 few seconds, will also have a prediction gap and other limitations.

1.3 BPS and design process

BPS provides relevant information which could drive critical decision-making at the early stages [2,151]. Architects and designers, who are involved from the early stages, make decisions about building form, facades, and material. But most of these decisions are intuitive with little or no support of energy simulation tools [31]. 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 [54,56,143,182,183]. Dynamic energy simulation tool such as EnergyPlus [54] or Modellica [182,184] have been integrated into an architectural modelling tool. The integration was focussed on minimising remodelling efforts by extracting information from the BIM model to develop BEM [55,185,186]. There are only few examples of such integration at the early stages [54,187]. 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 [42,47]. The integration of the ML energy predictions into BIM is another challenge which requires the extraction of design data for a specific ML model [66]. Few researchers proposed using sensitivity analysis methods to support decision-making for an energy-efficient building design [85,163,188]. 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

The article focusses on developing methods for quick energy predictions and compare design options at the early stages. We are developing a tool which extracts relevant information from the BIM tool, makes energy predictions, and compares design options. We assume a scenario in which the designer is interested in assessing options based on their energy performance. Designers are expected to develop a building envelope for each option. 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 predict energy use. The article ascertains 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 developed a BIM integrated tool to make energy prediction using various approaches. Primarily, we used one state-of-the-art approach and one alternative approach to treat uncertain parameters, create thermal zones, and energy predictions. These approaches are listed in Table 5.1. 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 predicts energy performance for a few hundred parameter combinations and uses statistical analysis for comparison. The core-and-perimeter-zones approach, proposed in ASHRAE standards, is used to create a detailed energy model [189]. The 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 used the alternative approach of ML models. One-zone-per-floor approach or ML models cause a prediction gap. We will be investigating these prediction gaps and their effects on comparing design options under uncertainty.

Table 5.1 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, decision-making at the early stages is complicated as designers need to assess design options on multiple competing criteria such as structural, energy, indoor comfort and others [97,98,134]. The article presents methods to compare design options for their energy performance, only.

2. Research methodology

The research methodology is presented in four subsections. 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 comparing design options. Section 2.4 describes implementation aspects of integrating the proposed methods into a BIM modelling tool.

2.1 Reference EnergyPlus simulation model

Both probabilistic energy predictions and developing ML model require data for several combinations of design parameters. However, it will be unrealistic to collect the real-world data for such a vast combination of parameters. Hence, we used a dynamic energy simulation tool, EnergyPlus (EP) for collecting data. We developed a reference EP model and calibrated it using measured heating and cooling energy requirements of a real building. The details of the EP model are documented in Appendix B. The reference model is developed considering the early design stage; thus, it uses the core-and-perimeters-zones approach for creating zones. The simulated energy requirement has a mean absolute error of 4.28% for heating and cooling energy predictions. In the article, the energy demand refers to energy provide heating, cooling, and lighting. Relevant design parameters are adjusted to generate the data for probabilistic predictions and develop the ML model. The researchers have developed an automated program, which quickly generates EP simulation models and runs parallel simulations to save time.

2.2 Details of different approaches used for energy prediction

Missing zone information and uncertainty in design parameters make energy simulation at the early stages a challenging task. High computational time required by dynamic energy simulations also needs to be reduced. We selected one state-of-the-art approach and one alternative approach to address each challenge. Figure 5.1 describes each challenge and approaches to address them. The first challenge is uncertain parameters and possible approaches are probabilistic and deterministic. The probabilistic approach uses Monte Carlo sampling to create many samples for predicting probabilistic energy demand and the deterministic approach uses mean values of design parameters to create one energy model for predicting deterministic energy demand. The probabilistic approach is a state-of-the-art approach to treat uncertain parameters while the deterministic approach is its alternative to reduce the computational time.

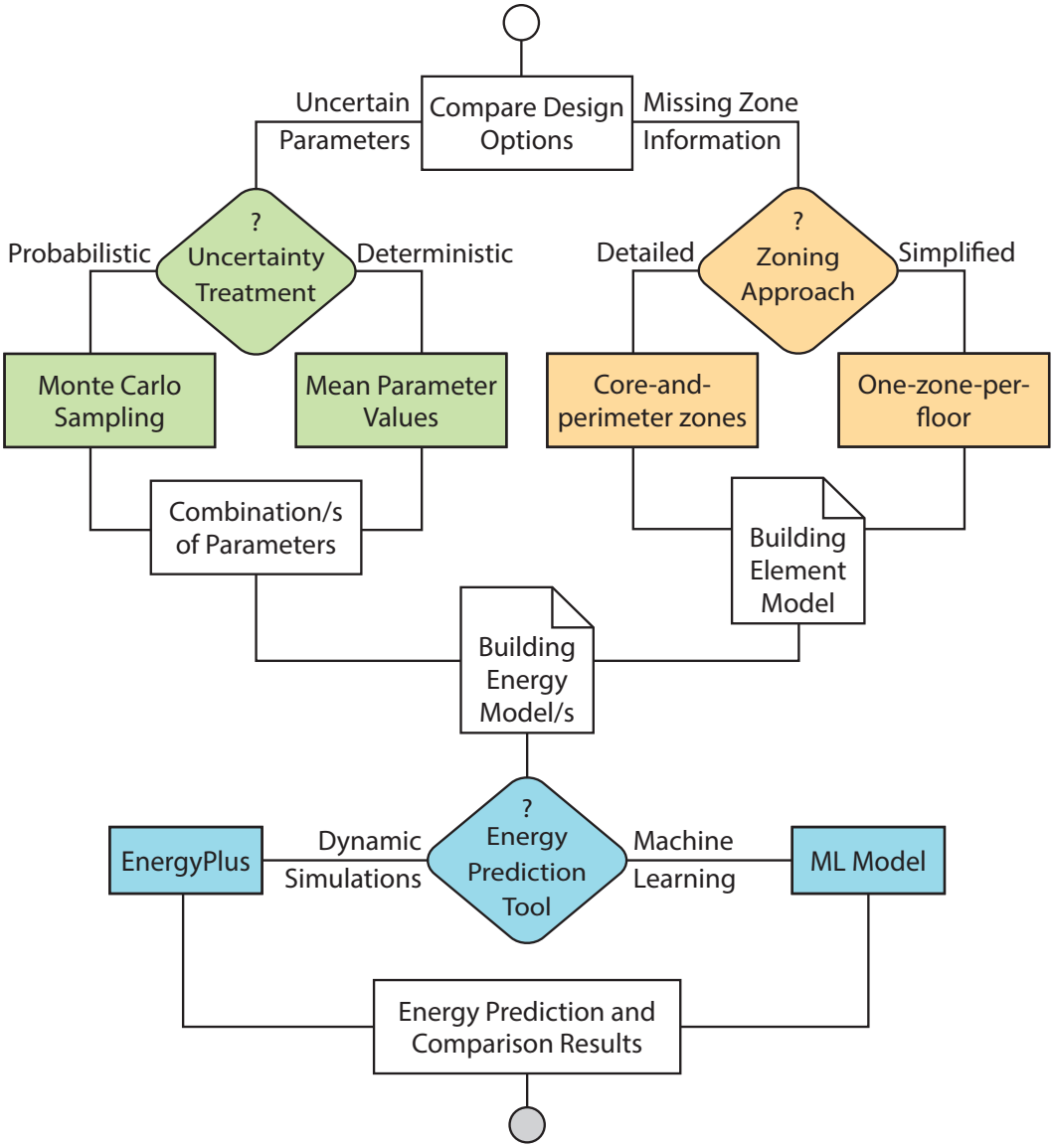

Figure 5.1 Primary and alternative approaches to energy prediction

The second challenge in missing zone information and possible approaches are detailed (core-and-perimeter-zones) and simplified (one-zone-per-floor). As stated earlier, core-and-perimeter-zoning provide more realistic energy predictions than one-zone-per-floor at a higher modelling and computational cost. The detailed approach is treated as state-of-the-art and simplified approach as its alternative. Following an approach to create zones, a building model with elements - walls, floor, and roofs, is created. A BEM is created using a combination of parameters and the building element model. Hence, we have one BEM for the deterministic approach and several BEMs for the probabilistic approach. The third challenge is to make energy predictions and possible approaches are dynamic simulations (EnergyPlus) and ML predictions. While dynamic simulation is the state-of-the-art approach and requires expensive computational efforts, ML predictions are quick and represent an alternative approach to reduce computational time.

While the state-of-the-art approaches provide reliable energy predictions, an alternative approach is preferred to reduce computational time. Hence, the article investigates whether alternative approaches are reliable enough to compare of design options at the early stages. If an alternative approach does not affect the decision-making and reduces the computational time, it will be preferred over the state-of-the-art approach. Subsections 2.2.1, 2.2.2, and 2.2.3 provide the details of the approaches.

2.2.1 Treatment of uncertainty in the parameters

The article categorises uncertain parameters in two categories - undecided parameters such as U-values, which will be decided at later stages and scenario parameters such as occupancy which will remain uncertain post-design. Uncertainty in the undecided parameters capture 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 conditions such as occupancy and light heat gain. The article considers all parameters that have effect of energy predictions but are not decided during the design phase as scenario parameters. We considered these parameters to study their effects on uncertainty in the energy predictions. Table 5.2 lists the undecided parameters and the scenario parameters, studied in the article.

Table 5.2 Details of uncertain parameters

Parameter category	Design parameters
Undecided 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 5.2. The first approach to treat uncertainty is “deterministic”. The energy demand is predicted for the mean values of uncertain parameters. The results using a deterministic approach are described by a

point prediction for each option. However, the point predictions do not consider the effect of uncertainty in the parameters. Thus, comparing options based on deterministic predictions requires an expert to account for the uncertainty. For simplicity, we assumed a variation of ±1.5% (an arbitrary value) energy predictions due to uncertain parameters. Hence, the energy prediction is visualised by the predicted value and variation, as shown in Figure 5.2. A threshold for the difference is required to conclude that two options have different energy performance. If a variation of ±1.5% is assumed; then, a difference of 3% in the deterministic predictions concludes that two options have different energy performance. A value of the threshold is extremely crucial to compare options under the deterministic approach. We will be discussing the effect of choosing a different value, later in the article. Comparing options under deterministic approach is performed, as shown in Eq. (1). Where E_{O1} and E_{O2} are the deterministic energy predictions for design option O1 and O2, respectively. $d_{O1,\ O2}$ is the percentage difference between E_{O1} and E_{O2}.

If $d_{O1,\ O2} < 3\%$ *(arbitrarily selected threshold)*
$\Rightarrow$ *Comparison results = No Difference (ND)*

Else if $E_{O1} < E_{O2}$
$\Rightarrow$ *Comparison result = O1 is better (O1)* ... *Eq. (1)*

Else
$\Rightarrow$ *Comparison result = O2 is better (O2)*

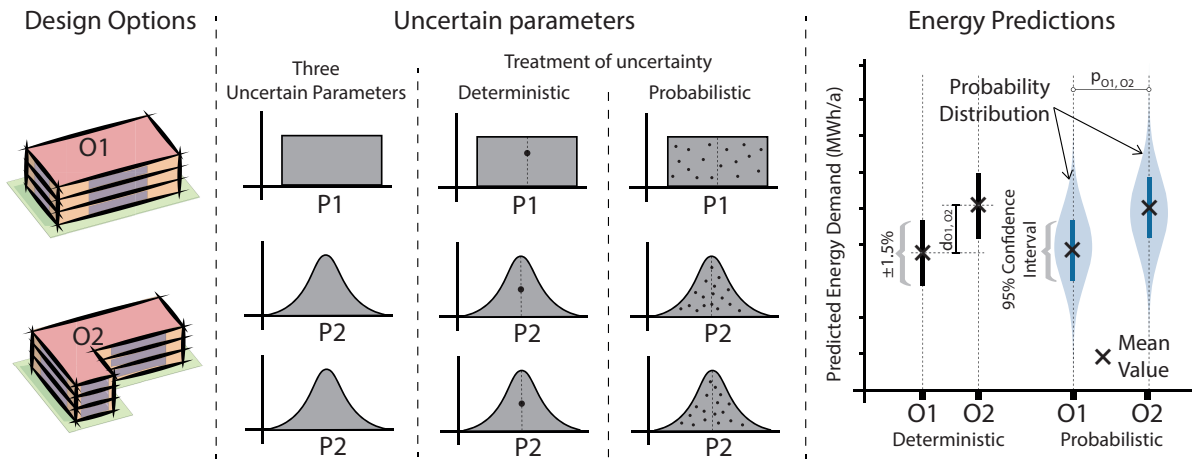

Figure 5.2 Different approaches to treat uncertainty in the parameters

The state-of-the-art approach to treat uncertainty is "probabilistic". In this approach, several random combinations are created by sampling uncertain parameters 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 5.2. The comparison is performed by statistical analysis and calculating the

probability value (p-value) for each comparison. The 95% confidence interval and the p-values are 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 shown in Eq. (2). Where E_{O1} and E_{O2} are energy prediction for design option O1 and O2, respectively. $p_{O1, O2}$ is the probability that the energy demand of the design options O1 and O2 are not different.

$$\begin{aligned} &\textit{If} \quad p_{O1, O2} > 0.05 \\ &\qquad \Rightarrow \textit{Comparison results = No Difference (ND)} \\ &\textit{Else} \quad \textit{if} \quad E_{O1} < E_{O2} \\ &\qquad \Rightarrow \textit{Comparison result = O1 is better (O1)} \\ &\textit{Else} \\ &\qquad \Rightarrow \textit{Comparison result = O2 is better (O2)} \end{aligned} \qquad \text{... Eq. (2)}$$

Statistical analysis – It is not possible to use probabilistic energy predictions for decision-making, directly. In probabilistic approach, the energy demand is predicted for several combinations of uncertain parameters and represented using a mean value and distribution. Hence, a statistical analysis is required to compare options using the probabilistic approach. Figure 5.2 shows the probabilistic energy predictions for two design options, O1 and O2. The p-value for each comparison is calculated using the Wilcoxon rank-sum test [190]. The 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 at least 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 at least 95% probability that the options have different energy performances. 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. (3) [191].

$$n = 21\frac{\sigma^2}{d^2} \qquad \text{... Eq. (3)}$$

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. Hence, the probabilistic predictions are performed using 400 samples (for two options) or 200 samples for each option.

2.2.2 Zoning strategy

The mass model represents a building at the early stages. 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 5.3. We selected ASHRAE's core-and-perimeter-zones to create a detailed zoning model [192]. In this approach, perimeter zones are created by offsetting each edge by a distance and a core zone in the centre. The approach represents a state-of-the-art approach as it provides the most realistic estimate of energy at the early stages [165,169,173,192].

We selected one-zone-per-floor approach as an alternative to create a simplified zoning model [66,172]. In this approach, one zone is created at each floor level. External walls, ground floors, internal floors, and roofs are generated using generic rules [66]. A window is generated in each external wall based on the window-to-wall ratio in that direction. 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/m^{2}K for internal walls. The approach requires fewer modelling efforts and computational time than detailed zoning. The energy simulation for a simplified model takes one-third of the time compared to a detailed model. However, the simplified approach may lead to wrong estimation of cooling energy and increases overheating risks; hence, a higher prediction gap than the detailed approach.

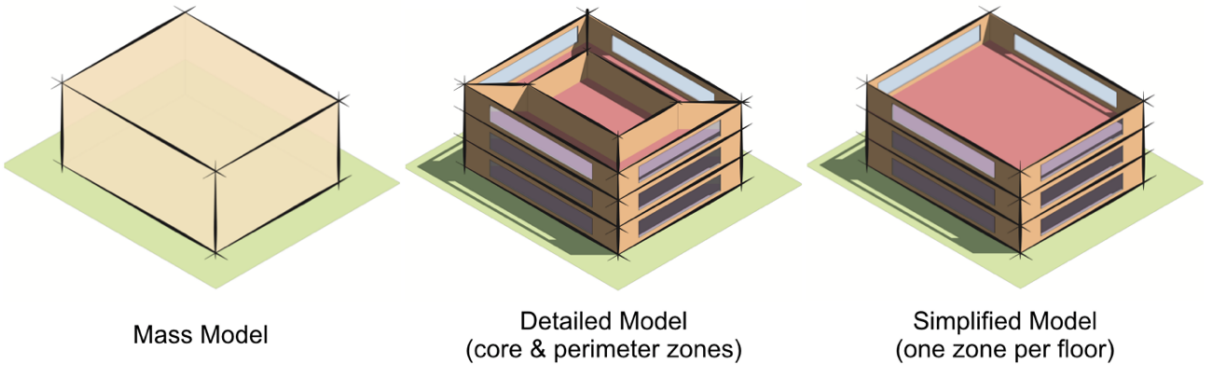

Figure 5.3 Detailed and simplified model from a mass model

2.2.3 Selection of energy prediction tool

Dynamic energy simulation is used as a state-of-the-art approach to predict energy demand. We are using EnergyPlus as a dynamic energy simulation tool [33]. As these simulations require very high computational time, especially in a probabilistic approach, an alternative approach of the ML model is used to make quick energy predictions. The article uses component based ML approach, proposed by Geyer and Singaravel, 2018 [42,47] and further developed in Chapter 3 to develop an ML model for the early stage energy predictions. Appendix E provides the details of training and testing the model. The ML model is trained using the Keras and TensorFlow library in python [130]. The model shows an accuracy of 0.94 (R^2) and root mean square error

of 4.2 MWh/a. The accuracy of the model is tested on random rectilinear building shapes and several combinations of design parameters. Thus, ensuring the applicability of the model on the possible design variations at the early stages. The ML model predicts the energy demand of 1000 building configurations within two minutes using a 16-core CPU having a clock speed of 2.4 GHz.

2.3 Comparison of approaches

We are studying the effect of alternative approaches on energy predictions and comparing design options at the early stages. The energy prediction and comparison results obtained using state-of-the-art approaches are treated as a reference. Thus, the article considers the method using of a probabilistic approach to treat uncertainty, detailed approach to creating thermal zones, and dynamic simulation to make energy predictions as the 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 5.3 lists all the proposed methods and the approaches used to make energy predictions.

Table 5.3 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 developed an automated tool to create BEMs from the BIM model; thus, the modelling takes a lesser time compared to other tasks. However, creating a detailed model requires a little more time than a 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 (M1) defines the accuracy of methods. An alternative method is said to have a 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 [142]. The plugin is developed to make BPS results available without any remodelling efforts and evaluate the proposed methods. The developed plugin allows selecting deterministic or probabilistic approach to treat uncertain parameters, detailed or simplified zoning strategy to generate thermal zones, and EnergyPlus or the ML model to

predict the energy demand. Figure 5.4 shows screenshots of the developed plugin. Different options are saved using a built-in function of Revit to manage design options. It expects the mass model for each design option at the early stages. Based on the zoning strategy, the plugin creates zones defined by walls, floors, and roofs. It extracts the geometrical information of building elements to provide input for different energy prediction tool. For example, it extracts the coordinates that define walls, floors, and roofs, to create EnergyPlus model. Similarly, it extracts the sizes of walls, floors, and roofs to provide input to the ML model. It further allows to define uncertain parameters using a user form. The numerical parameters are sampled and associated with the energy model in case of EnergyPlus simulation or as a numerical input to the ML model. The plugin also performs the pair-wise comparison of design options using statistical analysis in case of probabilistic approach to treat uncertainties. The plugin used two programming languages, C# for interacting with Revit and python for ML predictions and statistical analysis. The energy predictions and comparison results are integrated into the BIM tool by creating parameters and assigning a value to them. Thus, the developed plugin allows comparing design options using different energy prediction approaches in a BIM integrated environment.

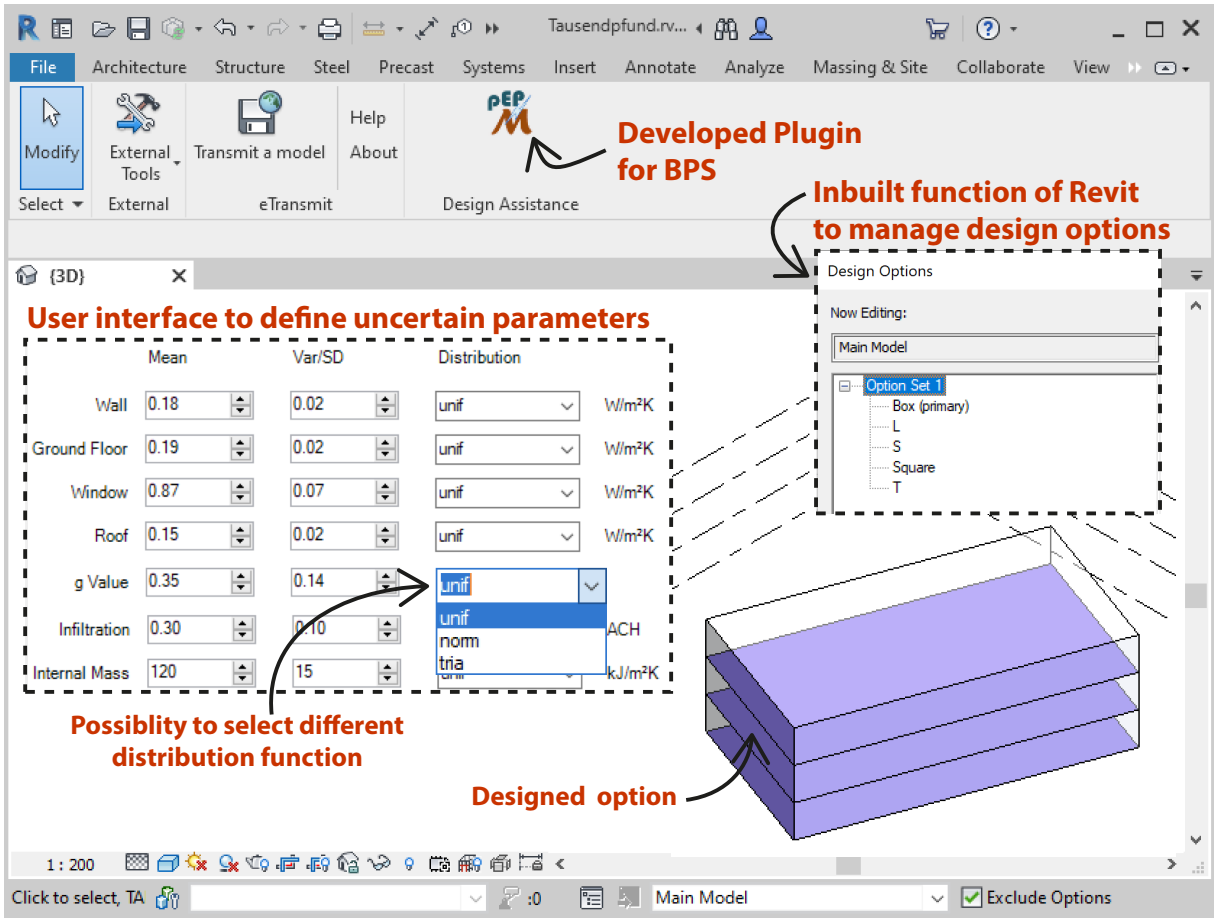

Figure 5.4 Screenshot from the developed Revit plugin

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 constructed building 'Tausendpfund' is shown in the top-left corner of Figure 5.5. Appendix B describes all the details of the simulation model. 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

We developed five design options of the constructed building to mimic the early stages. 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 5.5. These options represent the typical floor plans for office buildings [87,88]. Option 5 is introduced to represent the most compact shape among these options, which has a square floor plan. It should be noted that each option has three-storey and the same floor area. Besides the building mass model, designers developed a rough geometry of facades, from which the window-to-wall ratio (WWR) is the relevant information. In the constructed building, WWR is 0.3 in all the directions, which results in the total window to floor area ratio of 22.5%. Thus, we 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. Core and perimeter zones are created by offsetting the edge by 4.5 m, creating exactly one perimeter zone corresponding to each edge and one core zone, as described in Appendix C.

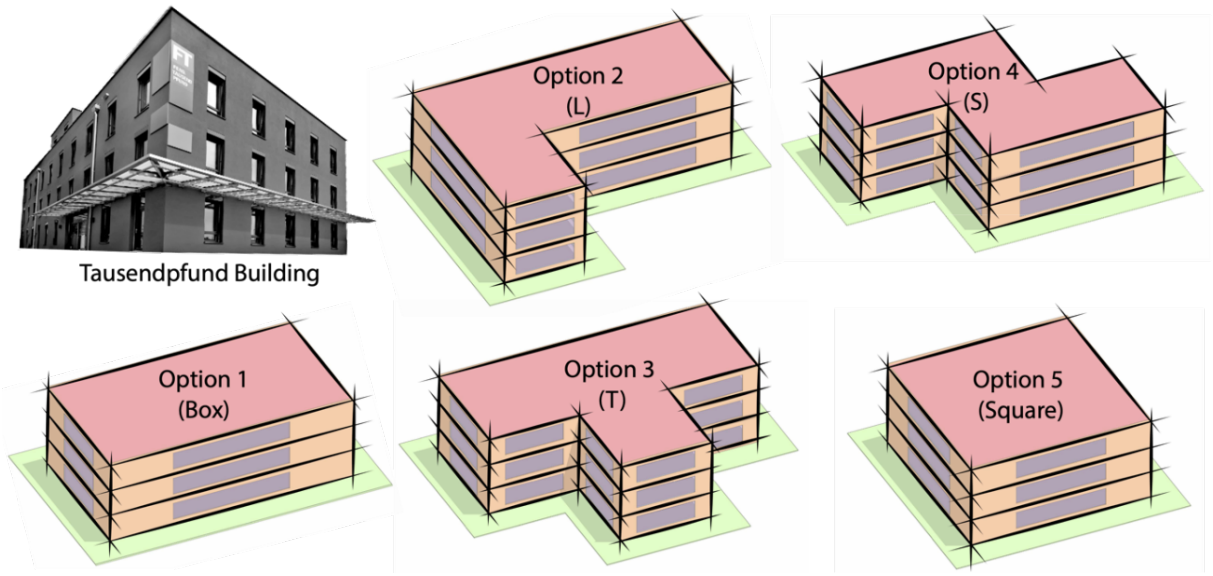

Figure 5.5 Description of design options

3.2 Uncertainty in the undecided parameters

The undecided parameters are decided at later stages. Since designers can select any value from the possible values, the uncertainty in these parameters is represented by a uniform distribution function [24,163,193]. A parameter has an equal probability of taking any value in the defined range. Further, we are keeping the mean value of these parameters as in the constructed building. The possible variations are assumed based on the thermal resistance requirements. Since the uncertainty in the design parameters will affect decision-making, we investigated two possible variations in these parameters. The two levels, high and low uncertainty, are used to represent the effect of different uncertainties on BPS results and further, comparing options. These parameters are listed in Table 5.4.

Table 5.4 Undecided design parameters - mean value and ranges

Parameter	Unit	Mean Value	Variation	
			High	Low
U-value (wall)	W/m^2K	0.18	0.02	0.01
U-value (ground floor)		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 constructed building has a U-value of 0.18 W/m^2K (walls), 0.19 W/m^2K (ground floor), and 0.15 W/m^2K (roof). These U-values are achieved by installing an insulation layer with thermal conductivity of 0.035 W/mK 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/m^2K for all opaque components [25]. EnEV standards specifies the reference U-values of 0.28 W/m^2K (walls), 0.28 W/m^2K (ground floor), and 0.2 W/m^2K (roof) [22]. 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 W/m^2K for high uncertainty and ±0.01 W/m^2K 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 W/m^2K. Based on the frame and glazed portion, a typical window have an overall U-value of 0.87 W/m^2K. 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 W/m^2K 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 W/m^{2}K and g-value of 0.21 (0.3 for low solar gain glazing). Thus, we assumed the U-values of windows is 0.87 W/m^{2}K and g-value 0.35 as mean. We assumed the possible variation of ±0.07 W/m^{2}K (U-value) and ±0.14 (g-value) under high uncertainty and ±0.035 W/m^{2}K (U-value) and ±0.07 (g-value) under low uncertainty.

Airtightness – DIN 18599 specifies an air permeability of 3 (category I), 6 (category II), 9 (category III) and 15 (category IV) for buildings [194]. 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 constructions in the article, as category IV construction represents the presence of apparent cracks and substandard from an energy-efficiency perspective. The constructed 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 furniture. Johra et al. have approximated thermal inertia of 30 kJ/Km^2 because of furniture in a medium-furnished office building [195]. We assumed ±15 (50%) under high uncertainty, and ±7.5 (25%) in this value as a correct estimate will not be possible. In simplified zoning models, an additional thermal mass of 90 kJ/m^{2}K is considered to simulate the effect of internal walls.

3.3 Uncertainty in scenario parameters

The scenario parameters are considered as targeted values by designers. These parameters are expected to follow a normal distribution as designers target for a mean value [24,30]. We have taken the mean value of these parameters as the constructed building and standard deviation (SD) of 10%. These parameters are mentioned in Table 5.5.

Table 5.5 Scenario parameters - mean value and standard deviation

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

The building has an average light heat gain of 6 W/m^2 to provide a lighting level of 500 lux, as required for office use. The building has an equipment heat gain of 12 W/m^2, as estimated based on the number of work and other equipment expected to be in the office. The building has a usual occupancy of 50 persons, which translates to approximately 24 m^2/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. The nominal coefficients of performance (COP)

are 2.8 for heating operation and 3.6 for cooling operation. The building has a boiler with a nominal efficiency of 0.95. We limit the value of boiler efficiency to 0.98, as a higher value will be unrealistic. We used nominal efficiencies as detailed modelling of HVAC system using seasonal energy efficiency ratios is impractical at the early stages.

4. Results

The results are presented in four subsections. Subsection 4.1 focusses on the energy prediction results using different methods and the prediction gap. Subsection 4.2 presents a comparison of design options using different energy prediction methods. Subsection 4.3 compares alternative methods against the reference method to observe the changes in the comparison results. Subsection 4.4 compares the energy prediction approaches based on time and accuracy.

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 used to observe the energy performance of the options and the prediction gaps. Figure 5.6 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 the reference method, methods M2, M3, and M4 have a prediction gap of 1.3 (2%), 3.0 (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.

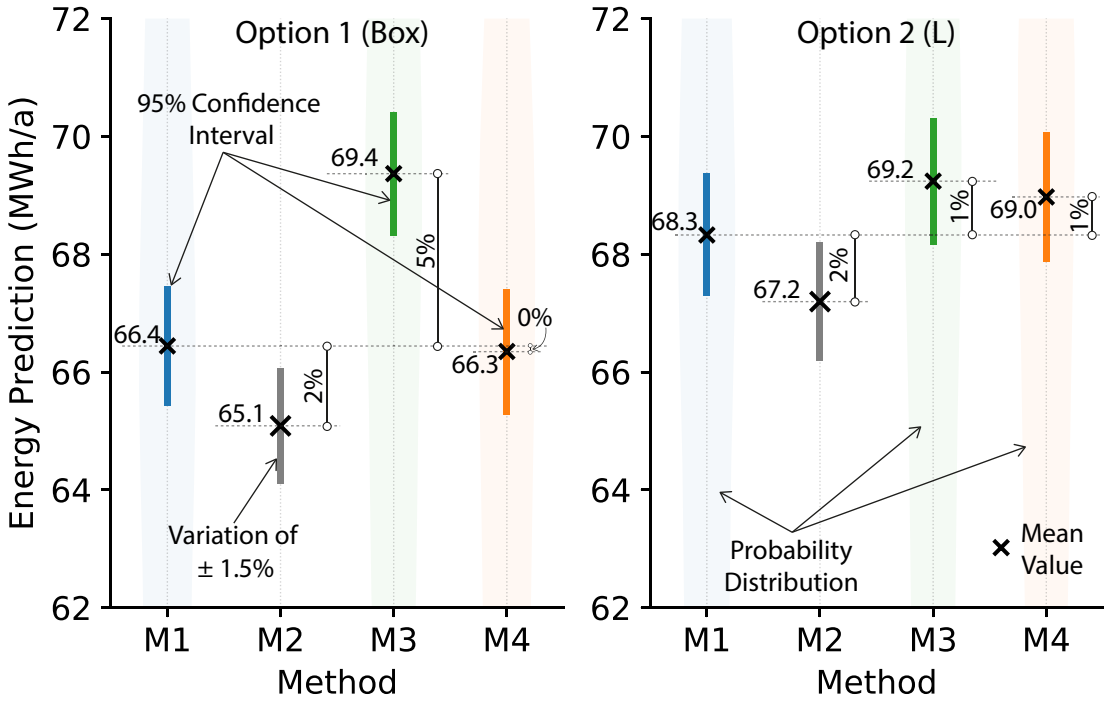

Figure 5.6 Prediction gap using different methods

It is worth noticing here that the prediction gap is the highest for method M3, which uses the simplified zoning approach. Moreover, 'Box' option has a higher prediction gap using M3 compared to option 'L'. A possible reason is better estimation of heating and cooling energy in the simplified model for option 'L' compared to 'Box' option. In simplified approach, 'Box' had one zone with its deepest point far from the facades compared to option 'L'. After observing the prediction gap for two specific options, we visualised the energy prediction results for all the options under two uncertainty conditions in Figure 5.7. It is not possible for designers to use the information from Figure 5.7 for comparing design options. Design options are compared using the methods, mentioned in subsection 2.2.1, and the results are presented in the next subsection.

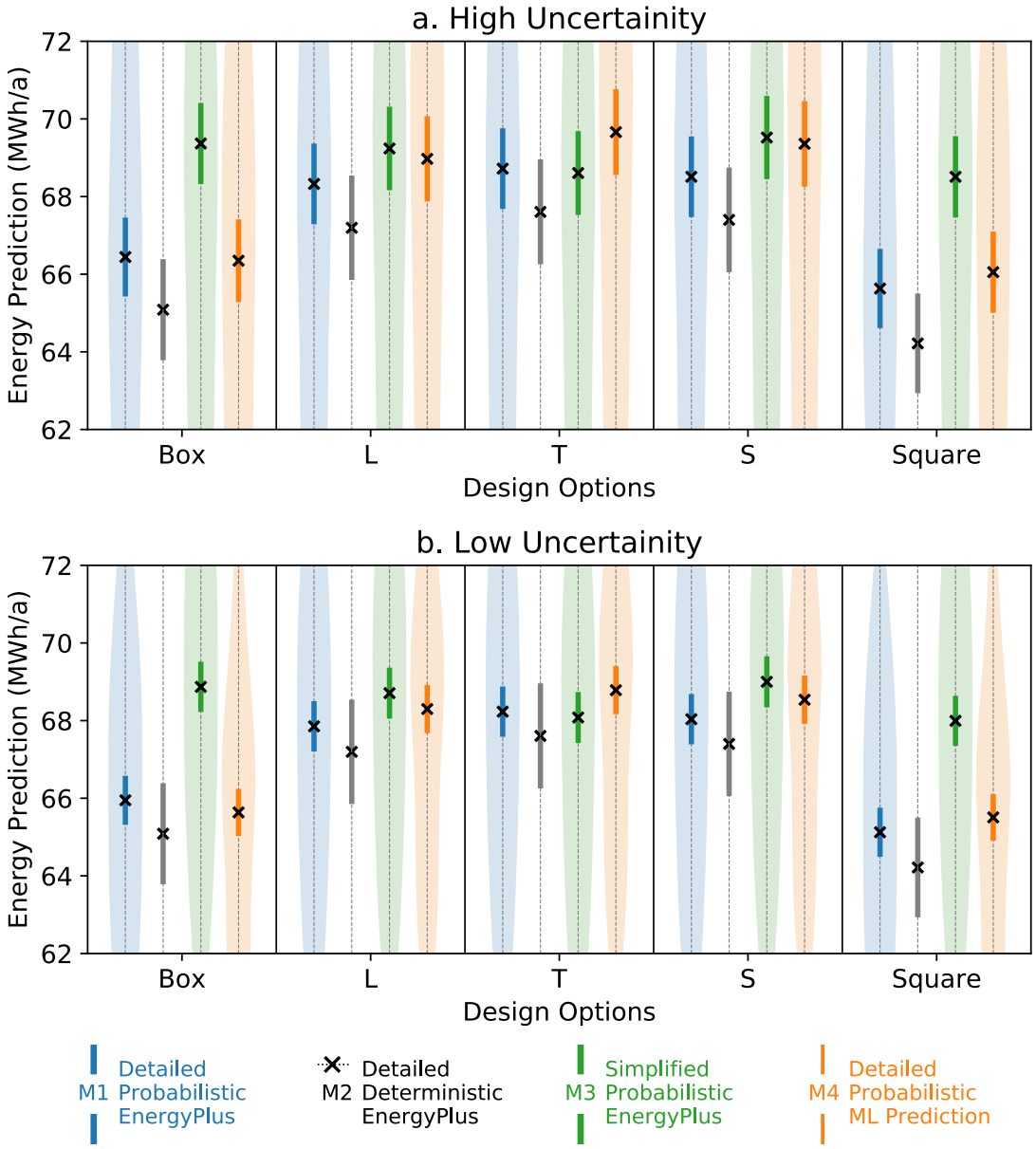

Figure 5.7 Energy prediction using different methods under high and low uncertainty

It is noticeable that energy predictions are more certain under low uncertainty conditions. For example, the 95% confidence interval under the high uncertainty for 'Box' option is 1.01 MWh/a, and under low uncertainty it reduces to 0.63 MWh/a. Similar trends are noticed for other options using any probabilistic energy prediction method.

Methods, M1 and M2, defer based on the approach to treat uncertainty. The mean value of energy predictions, using method M2, is always lower than method M1. The maximum prediction gap is 1.1 MWh/a, under high uncertainty and 0.6 MWh/a, under low uncertainty. Methods M1 and M3 defer based on the approach to create zones. 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 predicts a higher energy use than the detailed approach. Method M1 and M4 defer based on the approach to predict energy demand. The predicted energy demands using EnergyPlus, or the ML model are quite comparable, and the prediction gap is small. The maximum prediction gap is 0.9 MWh/a (1.3%) under high uncertainty and 0.5 MWh/a (0.7%) under low uncertainty.

The average value of 95% confidence interval for all the options 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 is more than this value. This observation suggests that 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.

4.2 Comparison of design options using different methods

The subsection presents the results of comparing design options using different energy prediction methods. There are five options which require ten pair-wise comparisons. Moreover, we have two uncertainty conditions, so the total number of comparisons are 20 for each method, as presented in Table 5.6. 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 the 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 a comparison, whether there is no difference (ND), or an option is better than other, is written in the brackets.

The comparison results using method M1 do not change under 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 the same energy performance based on the statistical analysis of probabilistic predictions.

For method M2, the comparison results are the same as method M1. However, we need to observe the differences in the mean energy predictions between two options. The highest difference is 5.14% 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. Hence, a value of 3% for threshold have all comparison results same as the reference method. A value of 4% for threshold will have 14 out of 20 comparison results same as the reference method and 5% for threshold will have only 10 out of 20 comparison results same as the reference method.

Table 5.6 Comparison of design options using different methods

Comparison of design options using method M1 (Probabilistic-Detailed-EnergyPlus)					
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 (Deterministic-Detailed-EnergyPlus)					
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 (Probabilistic-Simplified-EnergyPlus)					
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 (Probabilistic-Detailed-ML Model)					
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)**	***

Most of the comparisons using method M3 leads to no difference. In only two cases, it suggests one option is better than another. The large and varying prediction gaps for different options lead to different comparison results from the reference 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 not 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

The subsection 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 the reference method, as it uses the state-of-the-art approach to treat uncertainty, create zones, and predict energy demand. The changes in the comparison results, when using methods M2, M3, and M4, are presented in Table 5.7. If an alternative method has the same comparison results as method M1, it is marked with '✓' otherwise '×'.

Table 5.7 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→M4)					
Options	**Box**	**L**	**T**	**S**	**Square**
Box	***	✓	✓	✓	✓
L	✓	***	✓	✓	✓
T	✓	✓	***	✓	✓
S	✓	✓	✓	***	✓
Sq.	✓	✓	✓	✓	***

First, we compared the decisions using method M1 and M2, i.e., effect of using deterministic approach to treat uncertainty. There is no change in the comparison results. However, it should be noted that these decisions depend on the threshold set by an expert (3% in this case). Hence, it will change and may lead to wrong comparison results if the threshold is incorrectly set. There is no prescribed method to set the threshold. The value of threshold depends on the uncertainty in parameters and requires several observations. It will be an intuitive decision of experts to decide a threshold to conclude whether two options have different energy performances based on just one energy prediction under uncertain conditions. While comparing results from method M1 and M3, there are many different comparison results. The simplified model approach has only eight correct comparison results. The use of the ML model (M4) instead, EnergyPlus (M1) does not change any comparison results.

4.4 Comparison of energy prediction methods

The subsection compares different methods based on modelling time, prediction time, and accuracy. 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. The accuracy is the number of the same comparison results as the reference method M1. The proposed methods are compared in Figure 5.8. 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 requires the highest time for both modelling and prediction. In comparison, method M2, M3, and M4 require slightly less time. The prediction time is less for method M2, as it only requires one simulation for each design option. Method M4 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.

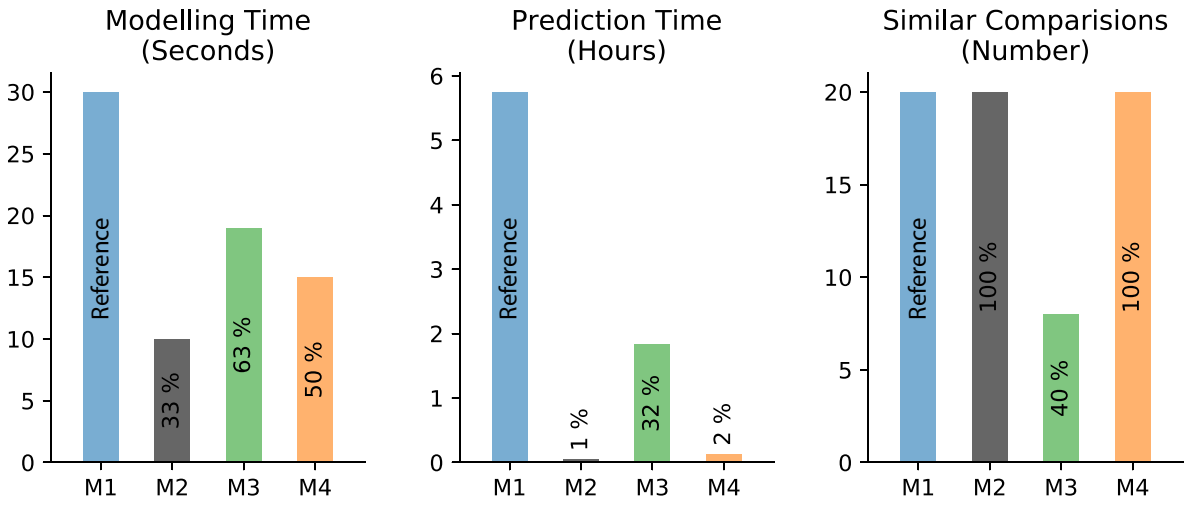

Figure 5.8 Comparison of different energy prediction methods

5. Discussion

The article presents different approaches to make energy prediction and compare design options at the early stages. It focussed on the issues of uncertainty, zoning, and high computational time. We selected one state-of-the-art and one alternative approach to address these 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 stages, the efficacy of an alternative approach is assessed using a test case building. A plugin for BIM tool has been developed to implement different energy prediction methods. BIM integration is required to manage design options and minimise any remodelling efforts required to create energy model. The design data from BIM model is used to generate EnergyPlus model and input to ML model. The method using a probabilistic, detailed model and EnergyPlus simulation approach provide the most reliable results and is treated as the reference method. An EnergyPlus model using a detailed model approach is developed and calibrated for the 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 exists a prediction gap. However, the 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 selected a small value of threshold (3%) to conclude that the energy performances of two design options are different. However, the threshold of 4% or 5% will change the comparison results, which will be incorrect in the situation under consideration.

The prediction gap caused by the simplified zoning approach instead of the detailed zoning approach is of particular interest here. For some options such as 'Box' and 'Square', the gap is more prominent than other options. Moreover, the gap increases to 2.9 MWh/a (around 5%), and it is negative for some options and positive for others. It makes using the simplified approach unreliable for comparing options. A large prediction gap with changing signs results in different comparison results from the reference method. 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. A detailed zoning approach provides more realistic energy prediction by dividing the floor area into smaller spaces. However, a simplified zoning approach uses only one-zone-per-floor that causes incorrect estimation of energy loads. By assuming no internal divisions, it treats the whole floor as one space exposed to outside in each direction which is not as realistic as a real building.

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 test case, the maximum prediction gap is only 0.9 MWh/a, which is the lowest among the three methods using the alternative approaches. Moreover, the prediction gap does not affect the results of comparing design options. Hence, the prediction gap caused by the ML model is 'small' enough to compare design options under uncertain conditions. The article assumes that pre-trained ML models are available during the design. However, time and expertise required to develop ML model also needs to be considered for such approach. ML model used in the article requires around 2-3 hours to collect simulation data and train them besides the ML expertise to oversee the development.

Observing the results of comparing design options and time-efficiency, method M4 appears to be a promising development. The method utilises the probabilistic approach to treat uncertainty, detailed approach to create zones, and an 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 the article is only tested for an office building with rectilinear floor plans, and weather data of Munich. However, research has been done to train the ML model for different weather data, too. More limitations on the values of parameters are documented in Appendix E. 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 rectilinear floor plans and the range of the parameters.

A plugin has been developed for BIM tool to make energy predictions without remodelling efforts. It implements different approaches to treat uncertainty, create zones, and predict energy using EnergyPlus or ML model. It further implements statistical analysis to compare design options under uncertainty based on probabilistic predictions. The tool processes the design information, and based on the selected approaches, it provides comparison results without additional efforts. So, the modelling time is minimal and primarily it requires time for simulations or ML predictions.

Further, the developed plugin is used to test the time-efficiency of the proposed methods. Besides the accuracy of comparison results, the time-efficiency is one of the essential aspects in selecting an alternative approach. We treated method M1 as the reference method which requires the highest modelling and prediction time. 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 large prediction gaps which results in different comparison results from the reference method. Method M4 requires little time for modelling and predictions and compares design options without relying on an expert. Same as method M2, this method has the same comparison results as the reference method.

Designers needs to assess the design options based on several competing criterion such as structural performance, aesthetics, and many more parameters. The article presents methods to only assess the options based on their energy performance. However, designers assign suitable weightage to various performance criterion based on the project requirements and select an option for further design development.

6. Conclusions

We presented four methods to predict energy demand for comparing design options at the early stages. The reference method uses previously developed state-of-the-art approaches to address the challenges of uncertainty, zoning, and computational time. Alternative approaches of deterministic predictions, simplified zoning, or machine learning (ML) are used to reduce the computational time. The deterministic approach provides BPS results in an extremely time-constraint situation; however, it needs an expert to compare design options under uncertainty. A simplified zoning approach should be avoided as it has a large prediction gap and fails to provide the same comparison results as the reference method. The ML approach to predict energy demand is time-efficient; but requires a pre-trained model. An ML model makes predictions for several design combinations within a few minutes. Small prediction gaps using the ML approach make the comparison results as reliable as dynamic simulations. However, the training time, data requirement, and the limitations of the ML model need to be assessed. In conclusion, time-constraint situations of the early stages require building information modelling integrated ML model to provide useful building performance results for energy-efficient building design. The future research works should focus on overcoming the limitations of the ML models and their seamless integration with BIM to provide quick and reliable BPS results.

********** *(end of the published article)* **********

Annexure D. Annexure to Chapter 5

The annexure discusses findings of the published article within the doctoral research context. The chapter serves to achieve the following subobjective:

- To determine the suitability of ML models for decision-making at the early stages.

The chapter used a test case of designing a medium-sized office building at the early stages. It studied the effect of prediction gaps associated with the alternative approaches on the decision-making. In the chapter's context, the decision-making refers to comparing design options. While the state-of-the-art method of probabilistic-detailed-dynamic simulation provide more accurate energy predictions, alternative approaches are needed at the early stages for reduced computational time. Machine learning (ML) approach reduces the computation time to around 2% of the time required for dynamic simulations, including data processing. The approach makes the same comparative assessment of design options as the dynamic simulations. Thus, the chapter concludes that the prediction gap caused by the ML model is 'small' enough for reliable energy prediction and decision-making at the early stages. ML approach provides a deliberate trade-off between time and accuracy. Similarly, the deterministic and the simplified zoning approaches also reduce the computational time at the cost of accuracy. However, the findings suggest that the prediction gaps are more significant for the simplified zoning approach and does not provide the same comparison results as the state-of-the-art approach. The deterministic approach provides the same comparison results as the state-of-the-art approach; but it needs an expert to account for the uncertainties.

The chapter studied whether the ML model make design decisions consistent with dynamic simulations at the early stages. Besides the ML approach to reduce the computational demand, alternative approaches of deterministic energy predictions and simplified zoning are also tested. It is found that only the ML approach does not affect the design decisions and provides results in a very short time. However, ML models require additional efforts and bring some limitations. The following points must be considered while considering ML models as a substitute to dynamic simulations:

1. ML approach requires a pre-trained ML model to make quick energy predictions. It requires additional time and efforts to collect data and developed the ML model. Besides time and efforts, developing models also requires ML expertise. Hence, the additional computational and modelling efforts need to be accounted for while discussing the advantages of ML approaches.
2. ML models are data-dependent that implies their accuracy is valid for the training and test design cases. However, the validity of ML models can be extended to cover more design cases by retraining and testing, as discussed in the chapter 3.
3. The chapter focussed on the building mass model and numerical design parameters such as U-value while considering design options at the early stages. However, designers will also

be interested in evaluating the effect of different energy saving strategies such as night ventilation, movable shadings, or underfloor heating. The ML models are not trained and tested for these strategies. The annexures of chapter 3 and 4 discusses the methods to extend the ML model for predicting the energy demand of the buildings with these strategies.

4. The chapter considered three alternative approaches to reduce the computational time. However, it does not study the alternative approaches of static and quasi-steady-state heat transfer equations. These alternative approaches also reduce the computational time and modelling efforts. Research has suggested with a few adaptations, quasi-steady state heat transfer equation can provide comparable results as dynamic simulations [177].

Conclusions with respect to the doctoral research objectives

The doctoral research has the objective of developing a quick design support tool using machine learning (ML), and the chapter contributes to it by assessing the appropriateness of ML models as a substitute to dynamic simulations. While pre-trained ML models are computationally inexpensive, the reliability of energy predictions and decision-making depends on the prediction gap. The chapter formalised the connotation of 'small' prediction gap that is used to define the appropriateness of ML models at the early stages. The ML model, used in the chapter, shows a root-mean-square-error of 4.2 MWh/a, and an R^2 value of 0.94. The ML model is around 50 times quicker and provides the same comparison results as the dynamic simulations. Hence, the chapter concluded that an ML model with a better accuracy or lesser generalisation errors than this model can be used to make reliable energy predictions and decision-making at the early stages. Further, the limitations of ML models and the time and efforts required to develop ML models must be considered while proposing them as a substitute to dynamic simulations.

6

Context-specific design support using ML and BIM

Chapter 6.
Context-specific design support using ML and BIM *

General introduction

The chapter has the objective to develop a tool that support early stage design decisions by providing holistic and context-specific information. The chapter achieves the stated objective by answering the following question:

? Which information is relevant for making energy-related design decisions, and how will it be provided in a short time?

Machine learning (ML) models are useful to provide quick probabilistic energy prediction results. However, the energy prediction results are just data, and designers need information to make design decisions. The previous chapter developed a method to quickly predict probabilistic energy performance and used a statistical method to compare design options under uncertain conditions of the early stages. The chapter extends the research work and develops a

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* The chapter has been published as the following article in a peer-reviewed journal:

M.M. Singh, C. Deb, P. Geyer, Early stage design support combining machine learning and building information modelling, Automation in Construction 136 (2022) 104147. https://doi.org/10.1016/j.autcon.2022.104147

The general introduction and annexure were not part of the published article and have been added to align its findings with the doctoral research objectives. Minor corrections have been made to the published article to address comments of the PhD committee.

The doctoral researcher has conceptualised, developed methodology and software tools, conducted formal analysis and investigation, visualised the results, and written original draft and made revisions. The second and the last authors have helped in visualisation of the results and writing the article.

design support tool to provide more holistic information for decision-making, such as design space exploration, energy analysis of design options, and sensitivity analysis. The developed method explores potential design solutions at any stage to provide relevant information. Since design changes affect the energy performance and potential solutions, the developed method should adapt to these changes and provide the context-specific information. For example, the sensitivity values will be higher for the U-value of windows if the design has more windows.

The chapter implements the developed ML models in an interactive web based tool – p-energyanalysis.de. It uses various open-source libraries and cross-platform applications to maintain the database of users and their projects, implement the developed ML models, and perform statistical analysis. The tool extracts design information from building information modelling (BIM) model to minimise the remodelling efforts. The developed tool adapts to design changes and provides quick, context-specific, and holistic information. The chapter tests usefulness of the provided information on a test case. Further, a few designers have been invited to use the developed tool on a design project. Their feedback has been collected to test the claim that the tool provides information for making energy-related design decisions.

Early stage design support combining machine learning and building information modelling

Abstract: Global energy concerns necessitate designing energy-efficient buildings. Many important decisions affecting energy performance are made at the early stages with little information. Dynamic simulations support informed decision-making; however, uncertainty, high computational time, and expensive modelling efforts impair their use at the early stages. The article develops an approach using building information modelling and machine learning that provides quick energy performance information. The approach has been implemented into a web tool, p-energyanalysis.de. It allows design space exploration, assesses the energy performance of design options, compares multiple options, performs sensitivity analysis, and tracks changes. Twenty-one participants (researchers and architects) used it as a support tool for designing an energy-efficient building. Their feedbacks are discussed as part of the tool development. The study found that the tool supports early stage design decisions by quickly providing relevant information. The limitations, such as the bias in the results towards training data population and implementation issues, are also discussed.

Keywords: building performance simulation; early design stage; BIM; energy efficiency; ML energy predictions; design space exploration; sensitivity analysis.

Introduction and background

Buildings use a significant portion of global energy, which prompted statutory authorities and institutions to promote energy-efficient buildings [68,95]. Previous studies showed that early design stages have a high potential to improve performance at a lower cost [9]. Design decisions at the early stages are primarily made using the rules of thumb or experience [96]. However, computational tools for building performance simulation (BPS) have changed this design paradigm, allowing decision-making based on engineering information [18,97]. While flexible building design at the early stages allows efficiently improving the performance, it makes assessing the effect of design decisions challenging using BPS. Sophisticated energy analysis packages that offer a high precision require a detailed energy model [150]. Developing energy models for continuously evolving or flexible design solutions is time-consuming and often deferred to compliance checking rather than design assistance [52]. While static rules of thumb do not capture the effect of changes in the design, sophisticated energy simulation tools are computationally expensive at the early stages.

Probabilistic analysis is vital to study the effect of design decisions (changing parameter) in flexible (uncertain) design conditions [75]. Such analysis requires simulating many possible solutions that increases computational time beyond the limits of the early stages [159,160].

Thus, a first step to gleaning any information for design assistance is to make quick energy predictions for several design possibilities. Since dynamic simulations will require too much time to predict energy performance, computationally inexpensive metamodels are required to predict energy demand at the early stages [52,196]. The energy prediction results require processing to provide interpretable and useful information for decision-making [135].

1.1 State-of-the-art approaches to address challenges to BPS at the early stages

Energy prediction is a cumbersome and time-consuming task for continuously evolving design. Researchers have identified three primary challenges to early stage energy predictions – uncertainty in the design, high computational time, and expensive modelling effort. Further, researchers have developed state-of-the-art approaches to overcome these challenges, as described in the following subsections:

1.1.1 Uncertainty in the design

The building design is evolutionary and iterative [197], i.e., most design parameters are flexible or unknown at the beginning. The flexibility or lack of information is expressed as uncertainty from the energy modelling perspective [13]. Several combinations of design parameters are evaluated to find a suitable value during the design process. Hence, energy predictions require a probabilistic approach by sampling the uncertain design parameters to make energy predictions [28,103]. Since a higher uncertainty in parameters translates to higher uncertainty in the energy predictions, designers need to reduce the uncertainty by focussing on important design parameters and detailing the design solution [126]. In this situation, the BPS results are valuable to assess the effect of changing design parameters on energy performance, i.e., sensitivity analysis. Further, comparing design solutions under uncertainty requires a statistical approach [99].

1.1.2 High computational time

A typical dynamic energy simulation takes around 2-5 minutes to simulate one model. Assuming probabilistic BPS results require around two hundred simulations, a day will be spent in the simulations. Several metamodeling approaches have been proposed to reduce energy prediction time [43]. Among them, machine learning (ML) has been used most extensively that promises to predict energy performance with a small prediction gap [38,42,47]. A large prediction gap will render BPS results unreliable [48]. Thus, it requires a well-generalising ML model covering early stage design cases and making correct energy predictions on design cases that are not included in the training data [94,198]. Developing a well-generalising ML model for early stage energy predictions is a topic of broader research that has been covered in several works, previously [46,47,87,94,123,199].

ML models are computationally inexpensive substitutes to simulation models with a slight loss of accuracy, representing a deliberate trade-off between time and accuracy [102]. Since most design information is uncertain at the early stages, BPS results are limited to comparing and

classifying design options rather than precise energy predictions [31]. It must be noted that achieving a high level of accuracy is time-consuming and unrealistic, as the design is uncertain at the early stages [34,161]. Thus, ML models are well suited for quick energy predictions at the early stages [103]. Steady or quasi-steady-state heat transfer equations are also alternatives to simulation models. However, these equations require adaptations, otherwise yield a high discrepancy in the results [177].

1.1.3 Expensive modelling efforts

Modelling efforts to translate design information to create an energy model is a significant barrier to the performance-oriented design at the early stages. Extracting design information from building information modelling (BIM) tools to create an energy model presents a promising prospect to reduce the modelling efforts [54,184]. However, this approach has been applied only to predict deterministic energy demand using simulation tools such as EnergyPlus [56] and Modelica [57,152]. Probabilistic energy predictions have been rarely coupled with BIM tools that require a novel approach to process uncertain design information and make predictions for several combinations [103,200]. The current approaches to obtain deterministic BPS results needs adaptation for probabilistic BPS results using ML models. Moreover, extracting information from the BIM model for energy predictions using ML models depends on its structure. For example, if an ML model uses building dimensions to make predictions, it requires extracting distances, but if it uses the building shape as input, the coordinates of building geometry are extracted. Once the ML model is combined with the BIM tool, it will make quick energy predictions aligned with the design process.

1.2 Limitations of the current approaches

Designers need energy performance information of many developed and probable solutions to support design decisions. Current approaches to obtain BPS results using ML and BIM merely provide data that requires processing into useful information. While these approaches provide energy performance of a design solution, designers are more interested in the effect of design decisions on the energy performance. Extracting such information is more challenging from probabilistic BPS results than deterministic results [103,201]. Without integrating sensitivity analysis or statistical methods into energy prediction tools, the results are not useful for decision-making.

BIM integration is vital to reduce remodelling efforts and obtain BPS results for continuously evolving design. However, current BIM-BPS integration solutions use deterministic approaches and dynamic simulations that are unsuitable for the early stages [54,182]. These solutions lack in capturing the flexible nature of the early stages. Moreover, dynamic simulations are time-consuming and require several assumptions to generate energy models from the BIM models. A few researchers developed integrated BIM-BPS solutions that provide optimised solutions [187,202,203]; however, optimised solutions are criticised for affecting designers' creativity to make design changes.

Previously, BIM integrated or standalone BPS solutions have been used for performance assessment [204], comparing several designs [103], design space exploration [205], sensitivity and uncertainty analysis [206], and optimisation [207–209]. While these studies serve their intended purposes, they do not provide holistic information for decision-making. Designers need various information such as sensitivity analysis, energy performances of possible design solutions, and the effect of making design decisions, all in a single design project. The lack of a comprehensive approach reduces the usefulness of the information in designing energy-efficient buildings.

1.3 Requirements of a design support tool

A decision support system is described as a system that provides all necessary information to support decision-making [210,211]. The limitations of current approaches, highlighted in subsection 1.2, substantiate the need for a decision support tool to provide holistic information for decision-making at the early stages. In the article, information refers to different results ranging from the probabilistic energy predictions of one or several design options to sensitivity analysis for assessing the effect of parameters on the energy performance. Gleaning such information requires integrating statistical and sensitivity analysis methods with the energy predictions. While energy predictions are merely data, a comparative assessment of design options, the effect of design parameters on the energy performance, and possible design solutions and their energy predictions is vital for decision-making. Moreover, the tool must provide all the information to use BPS results for designing energy-efficient buildings.

Usability, information management, and integration into the design process are critical for choosing a BPS tool and its successful implementation on a design project [212]. Thus, the developed tool must be integrated with a BIM tool to update BPS results with minimum remodelling efforts. Moreover, it must allow defining probabilistic design parameters and perform probabilistic energy analysis as required for the early stages. Designers' creativity is an essential aspect of architectural projects, and automatically designing an optimal solution affects designers' creativity. Hence, the proposed tool only provides information to support the energy-efficient design and relies solely on designers' creativity to make decisions.

Besides these features, the tool should allow users to experiment with design parameters and get context-specific feedback, quickly. Context-specific feedback differs from the generic feedback analogous to the conventional knowledge or the rules of thumb. For example, the effect of the window's U-value will be higher for bigger windows than smaller windows. Hence, the context-specific feedback is more reliable because the effect of design decisions changes with the design. The requirements of a design support tool can be summarised as follows:

1. The tool must provide various information such as possible design solutions and their expected energy performance, sensitivity analysis, and comparative assessment. It should provide only suggestive information and not limit designers' creativity to make changes.

Subsection 2.2 discussed the intended features of the proposed tool and the provided information.
2. The tool must allow updating building design from the BIM tool to minimise remodelling efforts. It must allow probabilistic design input and perform quick probabilistic energy prediction to meet the requirements of the early stages.
3. The tool should use a quick and integrated approach to provide context-specific feedback. It must allow designers to experiment with possible design solutions, interactively.

The above requirements are based on the literature review of using BPS results for energy-efficient building design and BIM-BPS integration. An essential aspect of developing such a tool is its efficacy in real-world applications. The tool requires testing on design projects, and the efficacy of provided information must be assessed in supporting the decision-making.

1.4 Research problem and objectives

Researchers have developed state-of-the-art approaches to address three primary challenges to energy predictions at the early stages – uncertainty, computational time, and modelling efforts, individually. However, these individual developments are insufficient to provide holistic information for making decisions. Designers need BPS information to understand the effect a design change on the energy performance. Moreover, the information from the BPS results must be interpretable to play an active role in making decisions. Hence, the researchers have developed a tool that uses design information from the BIM model, generates samples for probabilistic energy prediction, and uses an ML model for quick energy predictions. After predicting the energy demand, the results are processed to provide relevant information through an interactive user interface. The interface allows designers to define the design context, change design parameters, explore design space, analyse options, compare options, perform sensitivity analysis, and track changes. The tool provides dynamic feedback for the user-defined contexts different from the conventional static feedback. The tool is tested by independent researchers and practitioners to understand its benefits and shortcomings. The remaining article describes the development and testing of the support tool for designing energy-efficient buildings.

2. Research methodology

The article developed a tool that provides relevant information to support energy-efficient building design while addressing the three challenges to the early stage energy predictions. The first subsection, 2.1 describes implementation details of the methods to overcome these challenges. It is followed by a detailed description of the tool functionalities and typical design workflow in subsection 2.2. Subsection 2.3 describes the technical aspects of developing the tool. The last subsection, 2.4, provides the details of evaluating the tool's efficacy.

2.1 Methods to address challenges to early stage energy predictions

The three identified challenges to early stage energy prediction are uncertainty in the design, high computational time, and expensive modelling efforts. The following subsections describe

how probabilistic energy predictions are used to address the uncertainty, ML models are used to reduce the computational time, and BIM integration is used to minimise the modelling efforts.

2.1.1 Probabilistic energy prediction at the early stages

It is understood that energy predictions under uncertain scenarios require a probabilistic approach. A typical scenario of uncertain design parameters is shown in Figure 6.1. The parameters are sampled in the defined parameter space using random or quasi-random sampling schemes such as Monte Carlo, Latin hypercube, or Sobol sampling. Each of these sampling schemes have a few advantages and disadvantages. An energy model is developed and simulated for each sample to predict the energy demand. Finally, the probabilistic energy predictions are shown by mean, min, and max values and inter-quartile range.

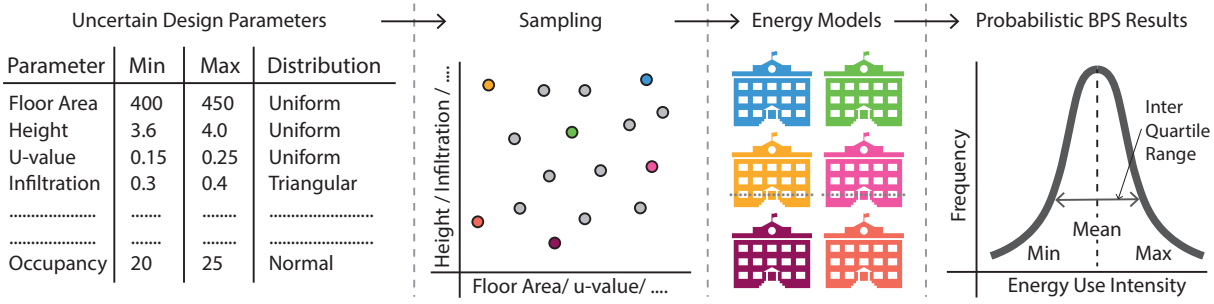

Figure 6.1 Probabilistic energy predictions under uncertain design scenario

A form is used to define probabilistic design parameters, as shown in Figure 6.2. A parameter is defined by a mean value, variation or standard deviation (SD), and distribution. A deterministic parameter is defined by setting the value of variation or SD to zero. [18,103] suggested uniform distribution for the parameters controlled by designers, triangular or normal for the uncertain design parameter with a target value.

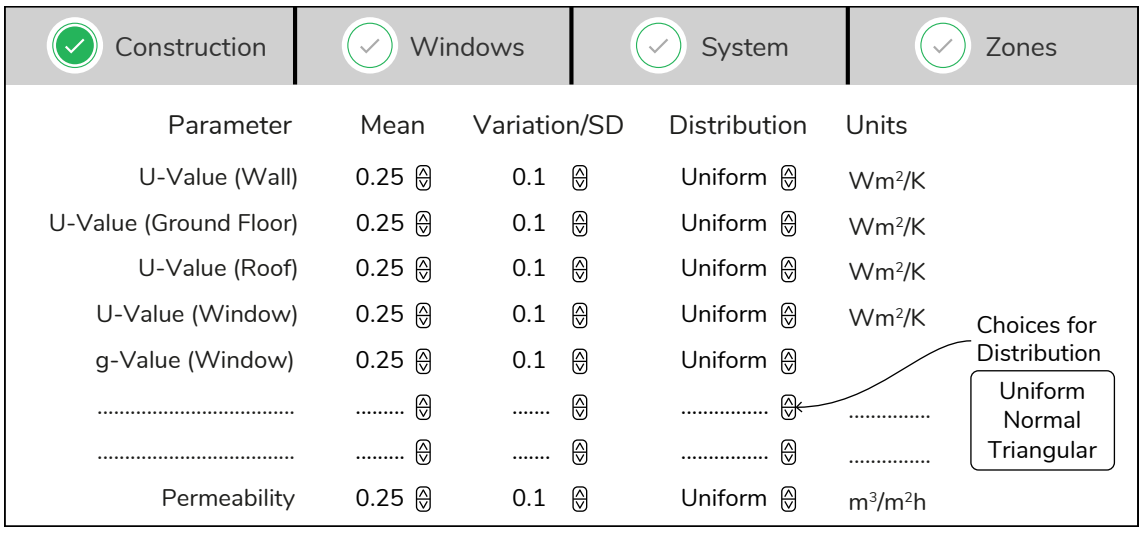

Figure 6.2 Form for defining uncertain design parameters

2.1.2 Machine learning for energy predictions

The article uses the previously developed convolutional neural network approach to train an ML model for energy predictions. More details of this approach can be found in [198] and Chapter 4. The process of data collection and training the ML model is documented in Appendix F. The parameters' ranges are different from Chapter 4. A dataset of 25000 random samples has been used for training. The accuracy of the ML model is estimated on a test dataset that consists of 1000 random samples, not included in the training dataset. Figure 6.3 shows the prediction accuracy of the ML model using scatter plot and error histogram. The ML model shows mean-absolute-percentage-error (MAPE) of 2.02% and root-mean-square-error (RMSE) of 1.66 kWh/m^{2}a. The scatter plot and the error histogram confirm that the ML predictions are close to the simulation values. Most samples are close to the black dashed line in the scatter plot, and taller bars are close to 0% in the error histogram. The goodness-of-fit or coefficient of determination (R^2) is 0.978. The predicted EUI accounts for energy to provide heating, cooling, and lighting.

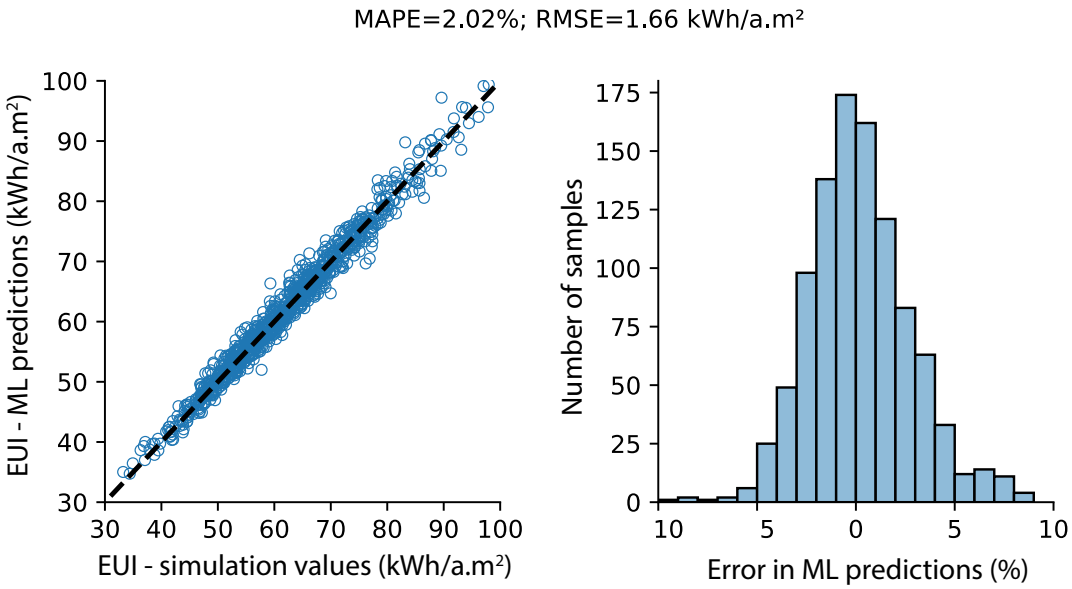

Figure 6.3 Accuracy of ML predictions on 1000 random test samples

2.1.3 Integration with BIM tool

Predicting probabilistic energy performance is integrated with a BIM tool, Autodesk Revit 2021 [142]. The integration reduces the modelling efforts by extracting the design information from the BIM model and processing it to generate energy models. Since the tool was developed for the early stages, only geometrical information is extracted from the BIM model, as shown in Figure 6.4. The web interface allows the user to probabilistic input parameters, as mentioned in subsection 2.1.1. The geometrical information from the BIM model and numerical information from the web interface is processed to provide input to the ML model and make probabilistic energy predictions. The tool also allows generating mass models in the BIM environment using the samples generated by the web tool.

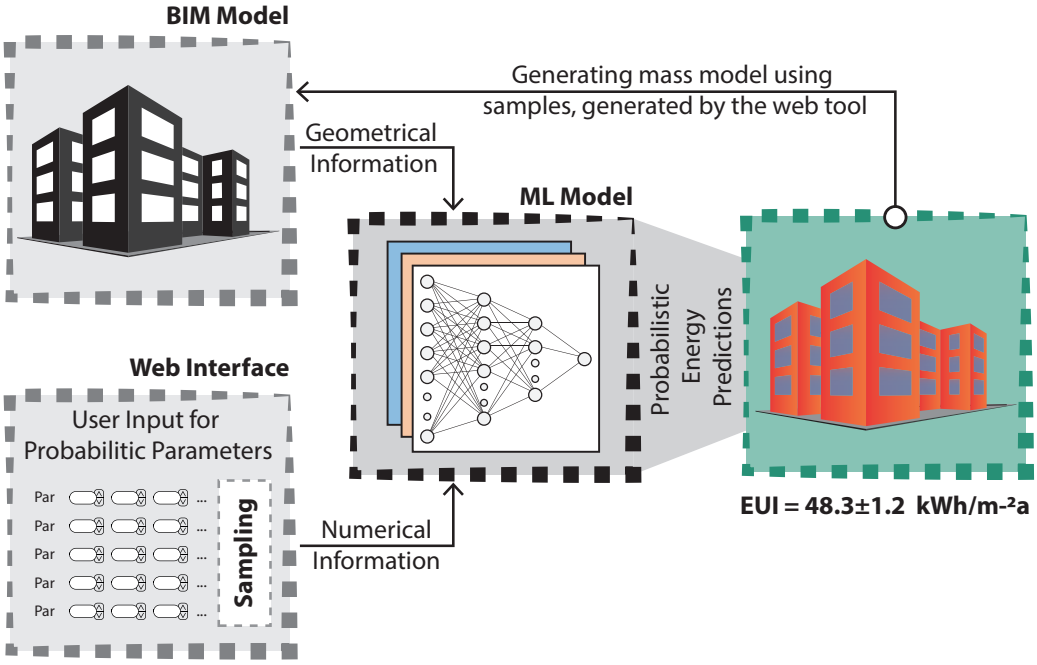

Figure 6.4 Integrating ML energy prediction model with BIM tool

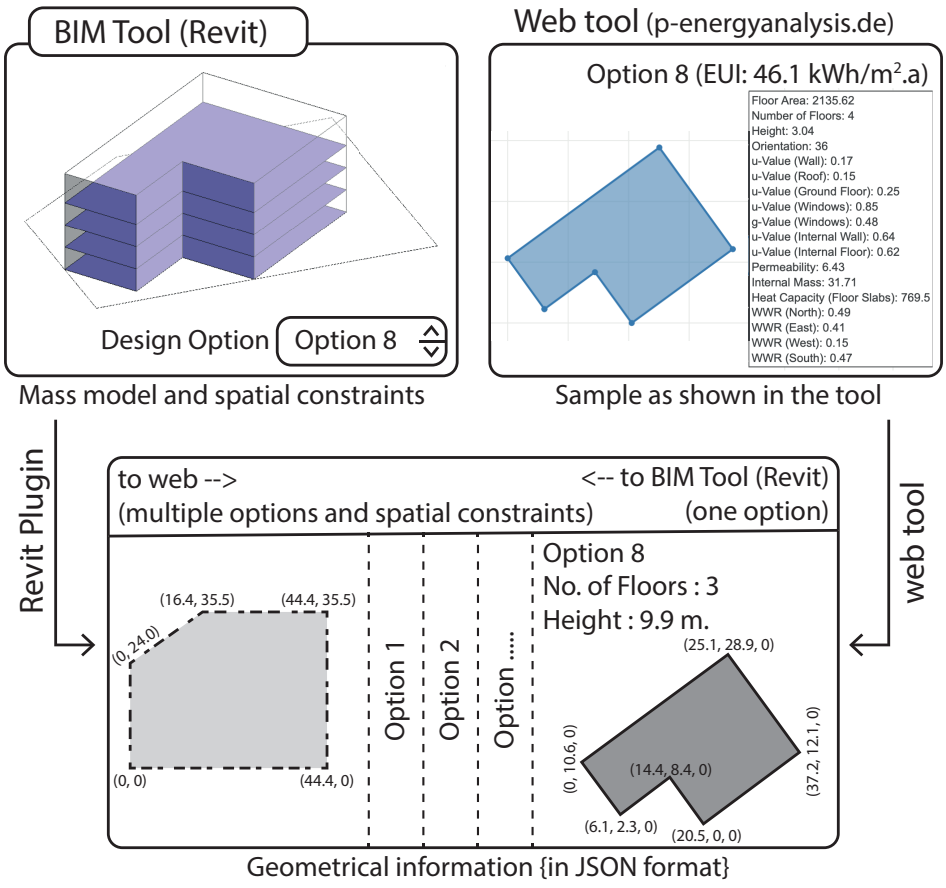

Figure 6.5 Information exchanged between the BIM and web tool

The BIM integration is different from the previous approaches as it uses the ML model instead of simulation tools to predict the energy demand. The ML model requires building footprint (as an image), number of floors, and height as geometrical inputs from the BIM model [198]. Figure 6.5 shows the details of geometrical information exchanged between the BIM tool and the web tool. It extracts the information of developed design options (mass models) and spatial constraints from the BIM model. A user models the spatial constraints as property lines, a built-in feature of Autodesk Revit. The spatial constraints are exported as a list of points. The mass model information is exported as its footprints (a list of points), the number of floors, and height. The information is exchanged using JavaScript Object Notation (JSON) files. JSON is an open-source, human-readable, and data interchange format supported by many programming languages. While exporting information from the BIM model, it exports all the design options and spatial constraints. While generating the mass model using the design option from the web tool, it only requires the geometrical information of one design option. The plugin to Autodesk Revit generates the JSON file for updating the project on the web and uses the JSON file from the web tool to generate the mass model.

Users are provided with a document explaining the tool's limitations and how to create a design option and mass model in Revit, available on p-energyanalysis.de. It is assumed that users create the mass model within the tool's limitation. The developed tool does not support some building designs such as courtyards, pitched roofs, or different floor geometry at different levels due to limitations of the ML model. Moreover, there is no adaptation proposed for these features as the effect of emulating such features with an alternative is unknown. Since all the components, ML model, Revit plugin, and the web tool are developed by the same researcher, the interoperability issues are diligently treated as exceptions to be addressed in future developments.

2.2 Intended features of the tool

The article develops a tool intended to provide relevant information supporting design decisions from an energy-efficiency perspective. Figure 6.6 shows a typical design workflow used to identify the intended features of the tool. A user starts with setting up a design context, i.e., requirements, property lines, and ranges of design parameters. The user identifies possible design solutions and their energy use intensity (EUI) at this stage. We refer to this step as "design space exploration". The user may create a new design option using a design space sample generated by the tool or by creating a design option using the BIM tool. At this stage, the user is interested in understanding how this option performs in the design context, i.e., EUI of the design option and its ranking among the design space samples. We refer to this information as "analysing an option". The next step is to improve the energy performance of a design option. The user will be interested in understanding which parameters should be modified to improve energy performance. The tool provides this information by performing "sensitivity analysis". It must be noted that the tool might point to an extreme value for a parameter for reducing EUI; however, it is a subjective decision of the user to adjust the

parameter based on several factors. For example, EUI can be reduced to a lower value by reducing the infiltration to the minimum; however, it may not be viable or practical. The tool allows saving a design option at each design decision. The user can retract these changes if the design is not progressing as intended. This functionality is referred to as "track changes". In the next step, the user has created multiple design options and like to understand which option has a better energy performance. This step has been referred to as "comparing design options".

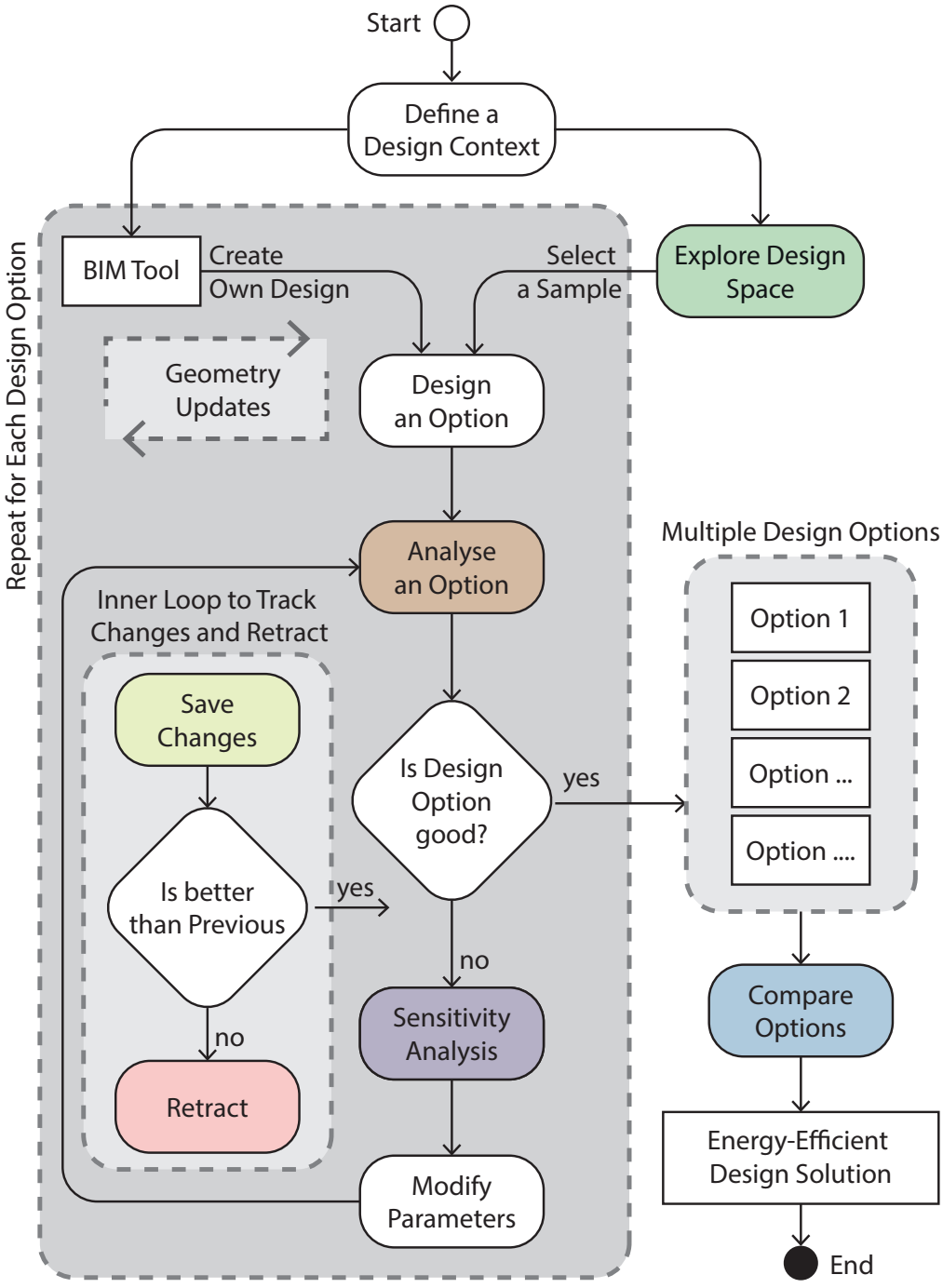

Figure 6.6 Typical building design workflow using the tool

Based on the typical design process, the tool has five features to provide the relevant information to support energy-efficient building design. The following subsections provide details of each feature:

2.2.1 Design space exploration

The objective of design space exploration is to provide a good starting point. The tool generates samples satisfying the constraints set by the user. The user defines the spatial constraints (using BIM tool), probabilistic design parameters (shown in Figure 6.2), and target EUI range. The parameters are sampled using the specified sampling scheme. Monte Carlo sampling scheme performs random sampling with no dependency among the sampled parameters. Latin hypercube sampling is quasi-random approach with constraints to evenly distribute a parameter along its range. Sobol sampling is not advised for sampling parameters for probabilistic predictions as it uses many constraints to distribute parameters, uniformly, which is not suitable for random sampling. Since the user has not created the building geometry, it needs to be generated based on the floor area requirement. Based on the sampled value of require floor area and the number of floors, a random floor plan is generated to create the mass model, as shown in Appendix C. The spatial constraints are used while generating random floor plans for design space samples. Different samples have different floor plans.

Figure 6.7 shows a typical design space exploration interface. The samples are uniformly distributed over the entire range of EUI, defined by the user. In the figure, the user has asked to generate 200 samples in the EUI range of 50-70 kWh/a.m^2. The range has been divided into five equal parts, i.e., 50-54, 54-58, 58-62, 62-66, and 66-70 kWh/a.m^2. The samples with EUI between 50-54 are categorised as A, 54-58 are categorised as B, and so on. These ranges are also used to categorise an option in the next subsection. The category shows the performance of an option in the design context and what is possible to achieve. The process of sampling and making energy predictions is repeated many times till the required number of samples are found that satisfy both the design and EUI constraints. The tool generates a sample, evaluates its energy performance, and assigns a category based on the predicted EUI. In this case, the process is repeated until each category has 40 samples. The tool allows visualising the sample's floor plan and the values of other design parameters and EUI. It further allows filtering the samples by adjusting the ranges of EUI and design parameters. The tool allows saving a selected sample as a design option and develop it using the BIM tool.

2.2.2 Analysing an option

Analysing an option predicts the probabilistic EUI of an option and ranks the option among the design space samples. The feature assumes that the user has created a design option (mass model), and the design parameters except geometrical, such as U-values, permeability, and system efficiency, are uncertain and defined, probabilistically. The tool samples the probabilistic design parameters based on their ranges and distribution. The geometrical information is integrated with sampled parameters to provide input for the ML model.

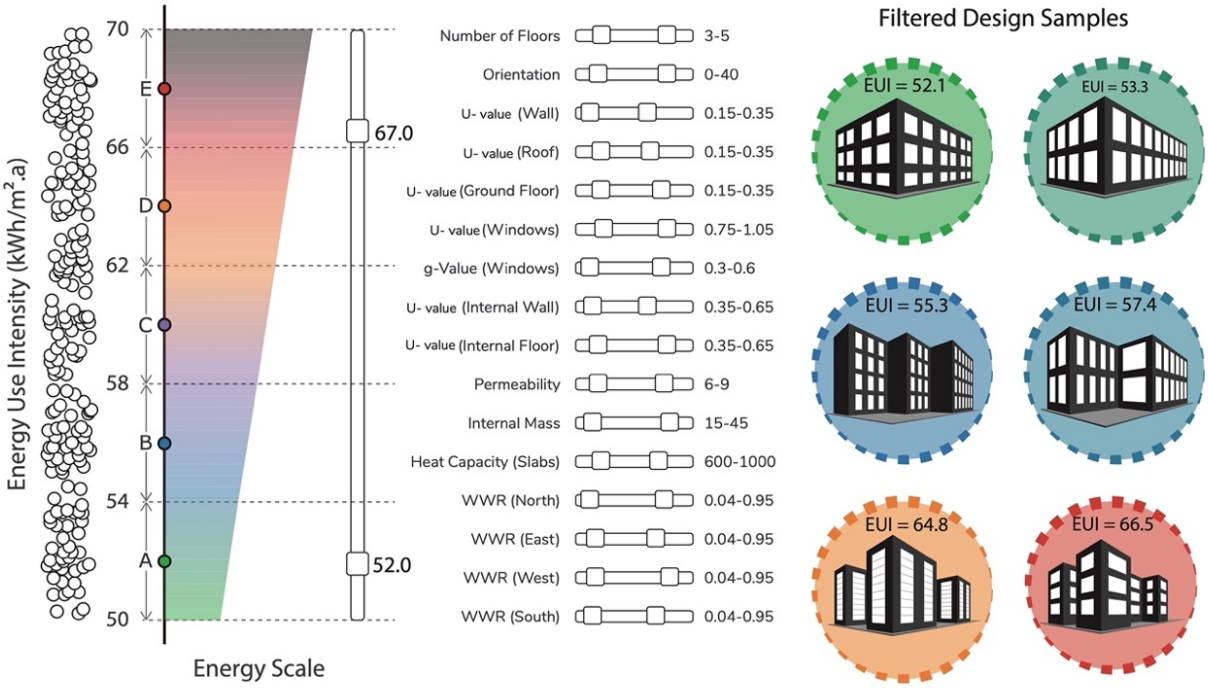

Figure 6.7 Design space exploration that allows filtering samples and visualisation

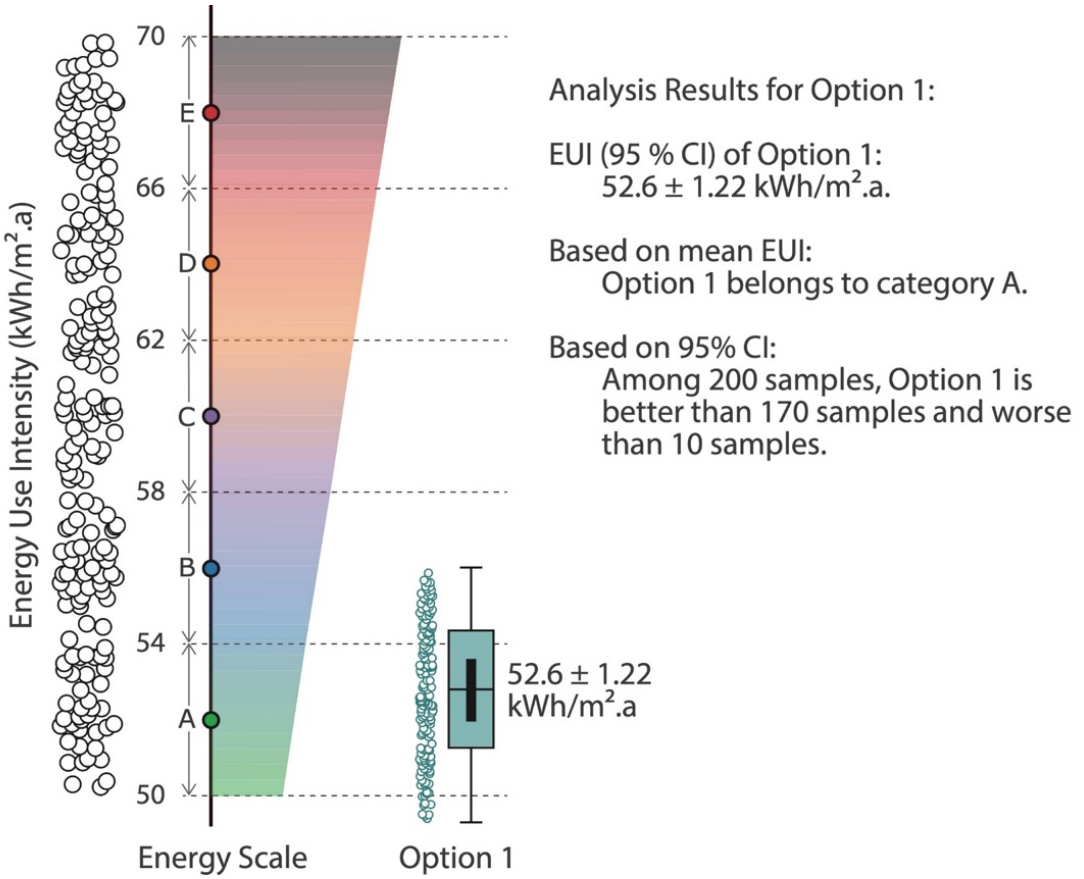

Figure 6.8 Analysing an option – its EUI and ranking among design space samples

After making the predictions, the performance of a design option is visualised against the possible solutions, as shown in Figure 6.8. The energy performance of the design option is shown by the box plot, representing extremes by the ends, and inter-quartile range by the box. The solid black line shows the 95% confidence interval. The mean value is used to determine the energy category of the option. 95% confidence interval is used to determine the ranking of the design option among the design space sample.

2.2.3 Sensitivity analysis

The feature provides sensitivity information for design space or an option. The sensitivity indices are calculated using a regression based method and represented by standardised regression coefficients (SRCs) [70]. We used SRCs to estimate sensitivities due to their ability to provide reliable results with a small number of samples [32]. The method approximates the model outcome by a multi-dimensional linear model with a regression coefficient for each parameter. The ability of SRCs to estimate sensitivities depends on the model's goodness-of-fit (R^2). [65] suggested R^2 of greater than 0.7 to achieve reliable SRCs. The article uses it as a threshold. A low R^2 represents the model's inability to capture higher-order interactions. A linear model also does not capture the effect of multicollinearity; however, the chance of any relationship among parameters is rare in random sampling.

Since SRCs are calculated for a specific design context, their assessment is more reliable than the generic rules of thumb. When the user changes the design context, i.e., the range of design parameters or the design option, their effects are reflected in the sensitivity values. As shown in Figure 6.9, the first option (a), which has bigger windows, has different SRC values than option (b), which has small windows. There is a significant change in SRCs for U-value (walls), U-value (windows), g-value (windows), and WWRs. Moreover, the effect of other parameters that are not directly related to windows, is also affected. These values can be used in both ways to reduce the EUI and the uncertainty in it. By reducing the uncertainty in the parameters with the highest absolute value, the uncertainty in EUI will be reduced by the highest margin. As shown in Figure 6.9 (a), permeability has the highest value of SRC; hence, reducing uncertainty in permeability, the uncertainty in EUI will be reduced significantly. The mean value of EUI can be reduced by reducing permeability as it is positively correlated and has the highest SRC.

2.2.4 Comparing design options

The feature performs a comparative assessment of several design options under probabilistic conditions. The tool allows creating multiple design options, each with a different mass model and probabilistic design parameters. The tool predicts the probabilistic EUI for each option, then visualises using a box plot and calculating probability values (p-values) using the Wilcoxon rank-sum test [190]. A p-value of less than 5% (0.05) is considered significant and concludes that the two options have different EUI; a better option is identified based on the mean value. The p-value of greater than 0.05 suggests no difference (ND) between the two options, and more details (less uncertainty) are required to compare.

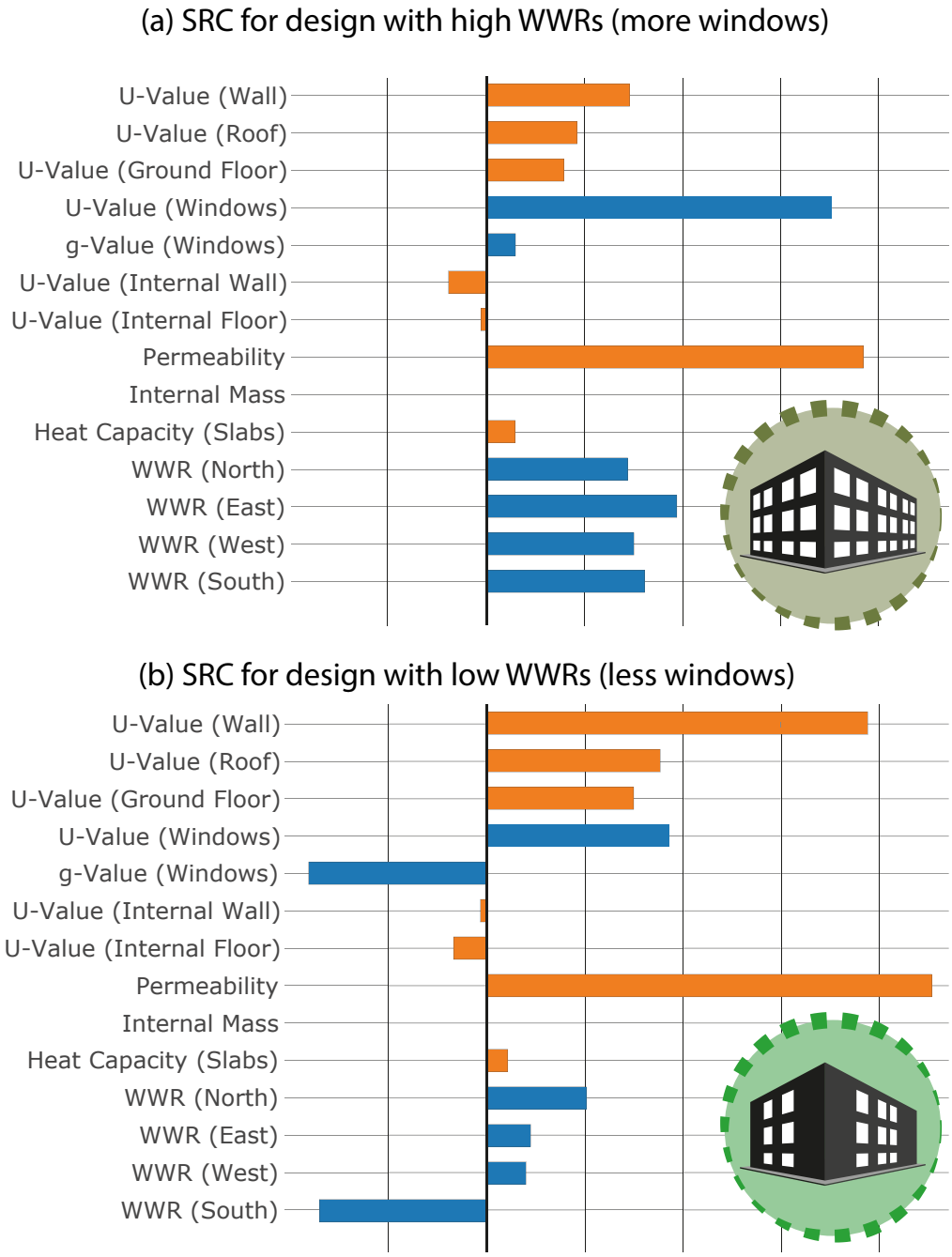

Figure 6.9 The difference in parameters' sensitivities for the two designs

As shown in Figure 6.10, the tool compares five design options based on their probabilistic EUI. The table shows p-values for comparing any two design options. For example, Op-1 performs better than Op-2; but Op-2 and Op-3 have no difference, based on their predicted EUI. p-values in the figure are rounded off to two digits; hence, 0.0 shows that the value is too small. [103] provides more details on comparing design options under uncertainty. A previous study suggests that 200 samples for each option are suitable for achieving the statistical power of 90% [103,191].

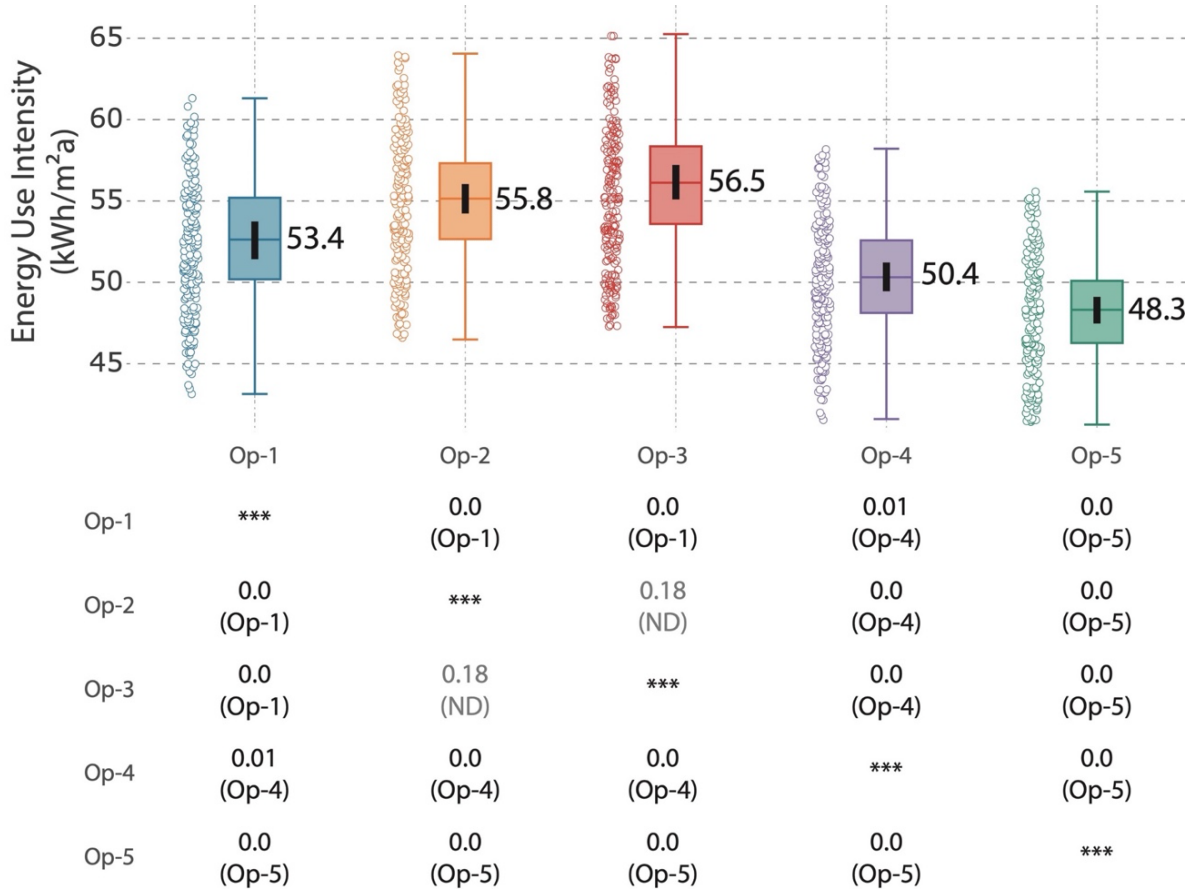

Figure 6.10 Comparing design options under an uncertain design scenario

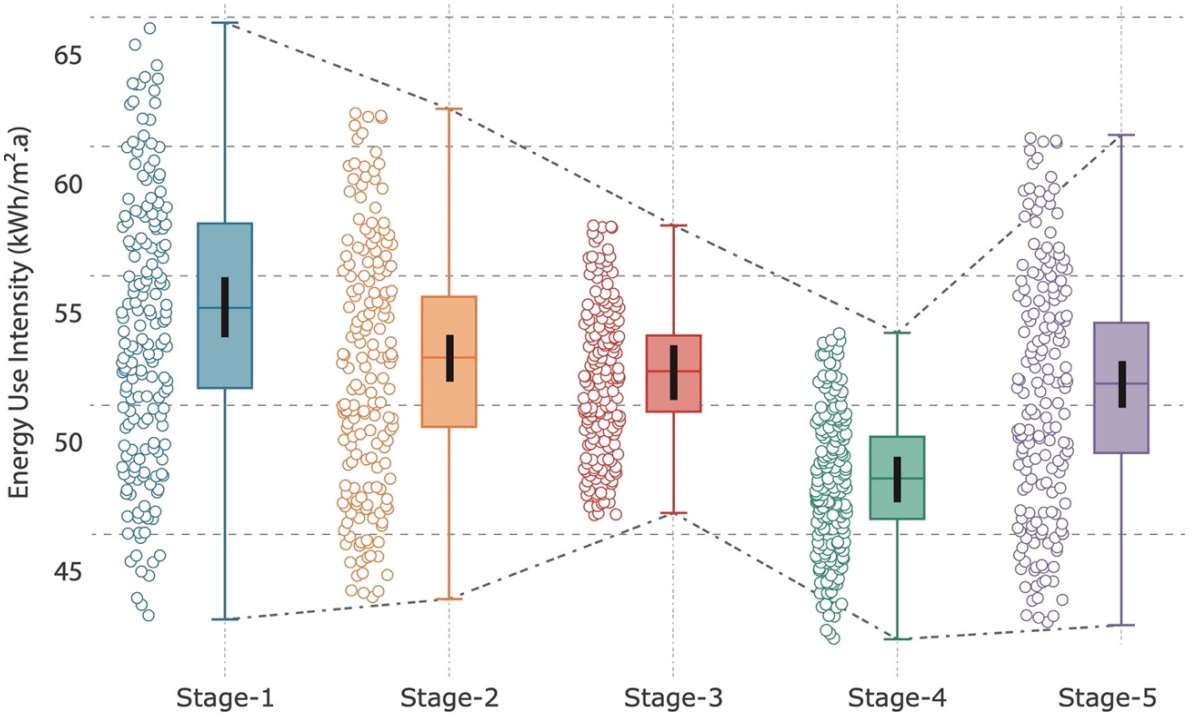

Figure 6.11 Tracking design changes based on probabilistic EUI

2.2.5 Tracking changes

The feature tracks design changes and the corresponding probabilistic EUI. The information ensures that the design is progressing in the correct direction. By making a design decision, the user expects to reduce EUI or uncertainty. However, incorrect design decisions will increase EUI or uncertainty. Any step that does not achieve the objective of reducing EUI or uncertainty needs to be backtracked, as shown in Figure 6.11. Design changes are tracked by recording the design and its probabilistic EUI. Figure 6.11 shows the design changes through five stages. From Stage-1 to Stage-2, the design has reduced both the uncertainty and EUI; however, from Stage-2 to Stage-3, the design has more details, i.e., less uncertainty but no change in the mean EUI. From Stage-3 to Stage-4, EUI has been reduced while the uncertainty in the EUI almost remains the same. Stage-5 shows an incorrect design decision that needs to be backtracked. Both EUI and the uncertainty has increased from the previous step. The tool allows the user to retract a design change to any saved design stages and progress in the right direction. The feature does not perform any analysis; it merely saves design decisions as a stage to track changes.

2.3 Development of the tool

Developing a tool that addresses all the challenges of early stage energy prediction and provides various energy performance information is challenging as it involves several concepts such as ML, statistical analysis, BIM integration. Figure 6.12 shows the technical details of the developed web tool. In the web tool, the client-side applications are platform-independent to make them available to many users, while server-side applications are Linux based to use many open-source libraries. It must be noted that the tool uses Autodesk Revit as the BIM tool, which runs only on Microsoft Windows. The server uses an SQL database for maintaining users' information and authentication. They can create, access, and update their project details saved as JSON files. The client-side application raises a jQuery request to access and modify the project information through the user interface. It uses Plotly to create interactive visualisation based on the information provided by the server. The update requests are categorised as without analysis and requiring energy analysis. An update such as creating or deleting projects or options and modifying design parameters do not perform any energy analysis. Such updates are handled using a PHP code that modifies the JSON files. Any request to update the energy analysis is handled using a C# and python code. C# code creates samples and passes information to python code that makes ML based energy predictions. It must be noted that the TensorFlow library used to create ML models is not available for C#; thus, the design information is passed to python code to make energy predictions. Further, Python code performs statistical and sensitivity analysis using open-source libraries, SciPy and scikit-learn.

The client-side application allows updating projects from Revit and generating a mass model in Revit using the design space samples generated by the tool, as mentioned in subsection 2.1.3. These tasks are performed by exchanging JSON files. The user needs to install the Revit plugin that uses a C# code to create JSON files by extracting design options information from the BIM

model. The user uploads this file to update the project. Further, to generate the mass model for a selected design space sample, the user downloads the JSON file containing mass geometry information, and the plugin creates the mass model.

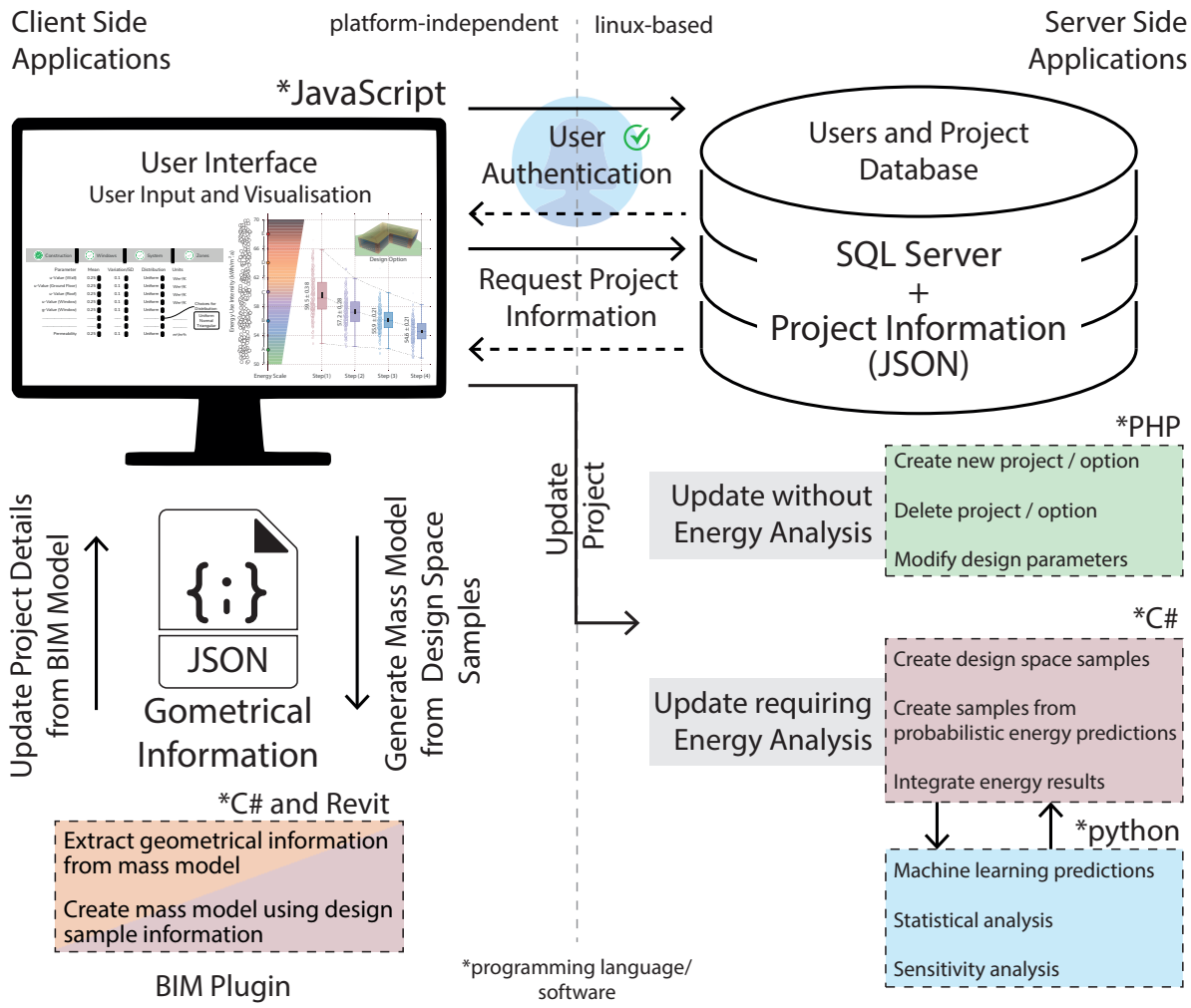

Figure 6.12 Technical details of the web tool (www.p-energyanalysis.de)

2.4 User feedback to test the tool's workability

The tool has been tested on a typical design process of an office building. Developing a mass model has been undertaken alongside finding a good range of technical specifications. The design task starts with initial design requirements, and users develop the design, further. The authors have invited 21 researchers and practising architects to use the tool on a design task. 10 out of 21 users are the professional acquaintances of the authors, and the remaining users belong to the extended network. All the invited users are trained in architecture (15 out of 21), building physics, or building energy analysis. The users' list includes 12 doctoral researchers, five practising architects, two post-doctoral researchers, and two graduate researchers. They all understand the BIM tools very well and have experience in computer-aided drawing. However, only six were proficient Revit users, while the rest were new to mass modelling in Revit. Their

objective is to design an energy-efficient building using the information from the tool. Their feedback is collected to understand the efficacy and shortcomings of the tool. A survey form is used to record their experiences on the Likert scale. The survey is intended to understand whether the information provided by the tool is useful, time-efficient, and aligned with the design process. They have also provided their subjective feedback to highlight the tool's shortcomings and information relevant to developing it. Their actions have been recorded to ensure that they used the tool for some time and count the number of times a feature has been called.

3. Results

The results are presented in two subsections. Subsection 3.1 presents the results of a typical design process of designing an energy-efficient building using the tool. This task is performed by the researchers that summarise the tool's usefulness in a design process. Subsection 3.2 discusses the users' feedback on the tool after using the tool for at least two hours.

3.1 Typical design process

An office building is used to demonstrate a typical design process. The article assumes a typical setting of the early design stage. Thus, the primary constraints are the site, building use, and initial settings of the design parameters. The site is assumed to be 45 × 45 m. square site and building use as an office—initial settings of other design parameters, as shown in Table 6.1. The user defines the EUI range and some important requirements such as floor area, number of floors, height, and orientation to define geometry. The user further defines other parameters that will be finalised later during the design such as, U-values, permeability, window-to-wall ratios (WWR). These parameters are considered uniformly distributed as the user can select any value from the possibilities. Number of floors is a discreet parameter and other parameters are continuous.

Table 6.1 Initial settings for design parameters (follow uniform distribution)

Parameter	Unit	Min	Max	Parameter	Unit	Min	Max
EUI target	kWh/m^2a	50	70	Number of floors	-	3	5
Floor area	m^2	1800	2200	Height	m	3.2	4.0
Orientation	degrees	0	45	g-value	-	0.4	0.6
U-value (Wall)	W/m^2K	0.15	0.25	Air Permeability	$m^3/h{\cdot}m^2$	6	9
U-value (Ground Floor)		0.15	0.25	Heat Capacity (Slab)	kJ/m^3K	0.6	1.0
U-value (Roof)		0.15	0.25	Internal Mass	kJ/m^2	15	45
U-value (Window)		0.75	0.95	WWR	-	0.05	0.95

A few parameters are considered outside of the design scope, such as occupancy. These parameters are related to building operation and remain uncertain during the design. These parameters have a target value; hence, selected to follow a normal distribution [18,103]. Table 6.2 documents such parameters, defined by a mean value and standard deviation.

Table 6.2 Setting for uncertain parameters (follow Normal distribution)

Parameter	Unit	Mean	SD	Parameter	Unit	Mean	SD
Operating Hours	h	11	0.5	Occupancy	m^2/Person	20	0.5
Light Heat Load	W/m^2	7	1	Heating COP	-	3.0	0.1
Equipment Heat Load		12	1	Cooling COP		4.0	0.1
Heating Setpoint	°C	20	0.1	Boiler Efficiency		0.95	0.01
Cooling Setpoint		26	0.1				

3.1.1 Selecting a starting design using design space exploration

Based on the defined settings, the tool generates 200 samples, out of which 20% (i.e., 40) samples with the lowest EUI are categorised under category A. The typical characteristics of these samples (EUI of 50-54 kWh/m^2a) are presented in Figure 6.13 (floor plan) and Table 6.3 (design parameters). The numbers next to the floor plan in the figure show the number of samples having a similar floor plan. As it can be noticed that most of the samples (around 25 samples out of 40) have a square floor plan. Eight samples have an L-shape, five have rectangular, two have a T-shape, and one has an S-shape floor plan. This information indicates that most samples with a low EUI have a compact floor plan. Table 6.3 documents the range of design parameters for category A samples. The range of a few parameters has changed from initial settings (highlighted in bold), showing that no samples meet the criteria of EUI outside this range. For example, floor area has a new range of 1900-2200 m^2 instead of 1800-2200 m^2, suggesting a more floor area tends to have a lower EUI. A similar interpretation may be drawn for permeability, i.e., samples with a EUI range of 50-54 kWh/m^2a have a permeability of 6.0 to 7.2 $m^3/h \cdot m^2$.

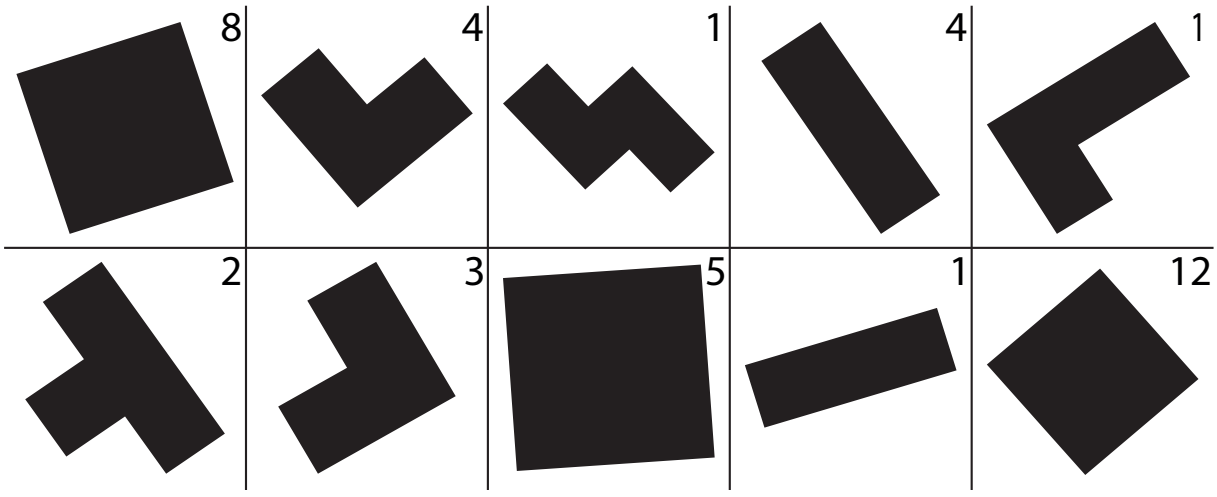

Figure 6.13 Typical floor plans for category A buildings

Table 6.3 Characteristics of samples in category A (EUI: 50-54 kWh/m^{2}a)

Parameter	Unit	Min	Max	Parameter	Unit	Min	Max
Floor Area	m^2	**1900**	**2200**	**g-value**	**-**	**0.42**	**0.6**
No. of Floors	-	**4**	**5**	**Air Permeability**	**m^3/h·m^2**	**6.0**	**7.2**
Height	m	**3.2**	**3.6**	**Heat Capacity (Slab)**	**kJ/m^{3}K**	**0.6**	**1.0**
Rotation	degrees	0	45	Internal Mass	kJ/m^2	15	45
U-value (Wall)		0.15	0.25	WWR (north)	-	0.12	0.69
U-value (Ground Floor)	W/m^{2}K	0.15	0.25	WWR (east)		0.11	0.67
U-value (Roof)		0.15	0.25	WWR (west)		0.1	0.82
U-value (Window)		0.75	0.87	WWR (south)		0.12	0.87

3.1.2 Design development by analysing an option, sensitivity analysis, and track changes

This step assumes that the user developed a design option and details it further to reduce EUI or uncertainty. In this iterative step, the user makes design decisions to improve the energy performance. A typical iteration involves the following tasks:

a. Modify design parameters
b. Run probabilistic energy analysis
c. Analyse an option in the design context
d. Save an option as a design stage (use to track changes or retract to the previous stage)
e. Run sensitivity analysis
f. Adjust design parameters - a design decision

Table 6.4 Stepwise decisions to design an option

Parameter	Unit	Step (1)	Step (2)	Step (3)	Step (4)
U-value (Wall)	W/m^{2}K	0.15-0.25	0.15-0.25	0.15-0.25	**0.16-0.18**
U-value (Ground Floor)		0.15-0.25	0.15-0.25	0.15-0.25	**0.16-0.18**
U-value (Roof)		0.15-0.25	0.15-0.25	0.15-0.25	**0.16-0.18**
U-value (Window)		0.75-0.95	0.75-0.95	**0.75-0.85**	0.75-0.85
g-value	-	0.4-0.6	0.4-0.6	**0.5-0.6**	0.5-0.6
Air Permeability	m^3/h·m^2	6.0-9.0	**6.0-7.0**	6.0-7.0	**6.0-6.6**
WWR (north)	-	0.2-0.6	0.2-0.6	**0.3-0.5**	0.3-0.5
WWR (east)		0.2-0.6	0.2-0.6	**0.3-0.5**	0.3-0.5
WWR (west)		0.5-0.9	0.5-0.9	**0.6-0.8**	0.6-0.8
WWR (south)		0.5-0.9	0.5-0.9	**0.6-0.8**	0.6-0.8
EUI (95% CI)	kWh/m^{2}a	59.5±0.38	57.2±0.28	55.9±0.21	54.6±0.21

Table 6.4 and Figure 6.14 show the development of a design option through four design steps. The first step uses the initial set of design parameters; then, the user adjusts the parameter/s with a high SRC value (shown in Figure 6.15).

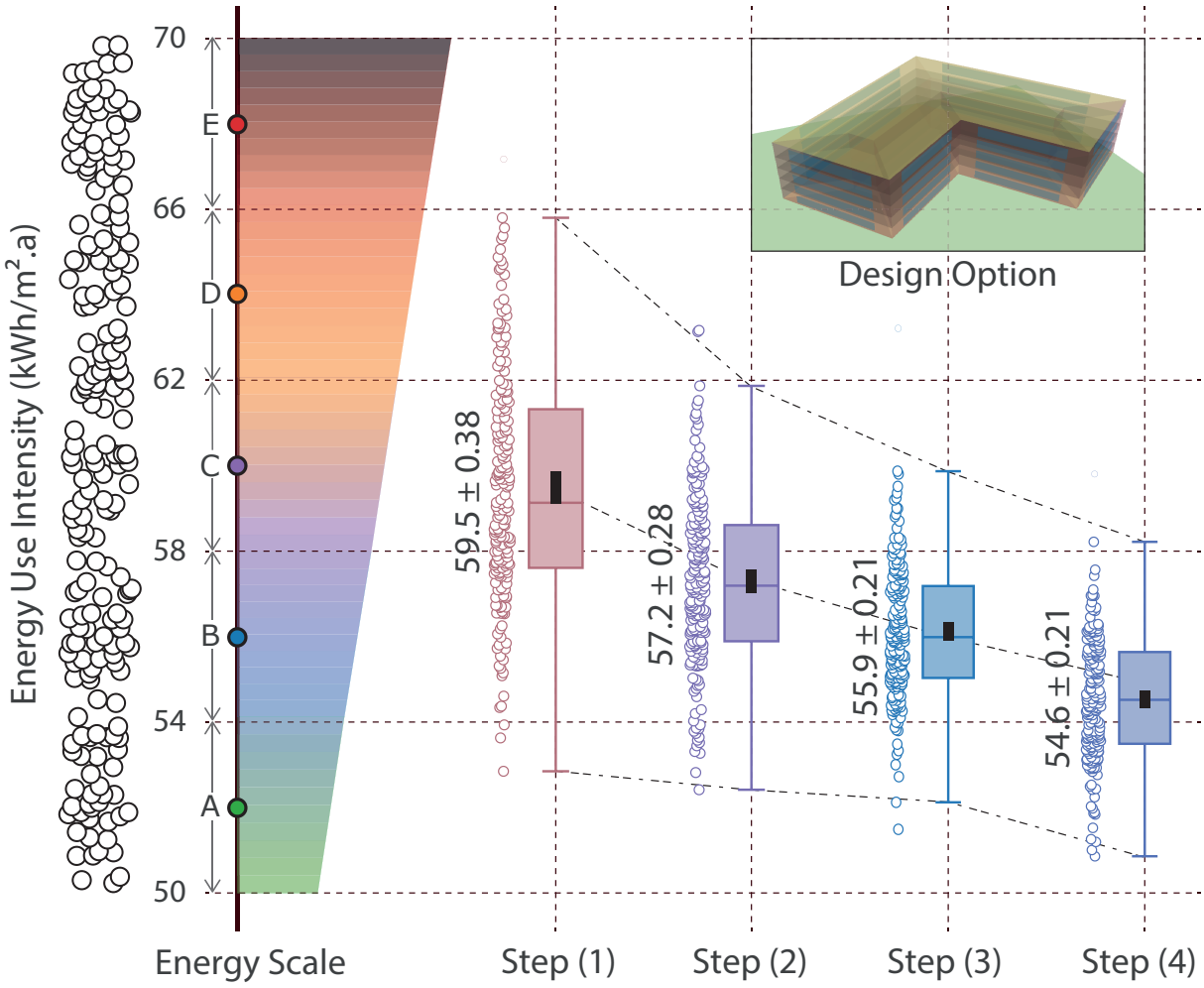

Figure 6.14 Analysing an option and tracking changes

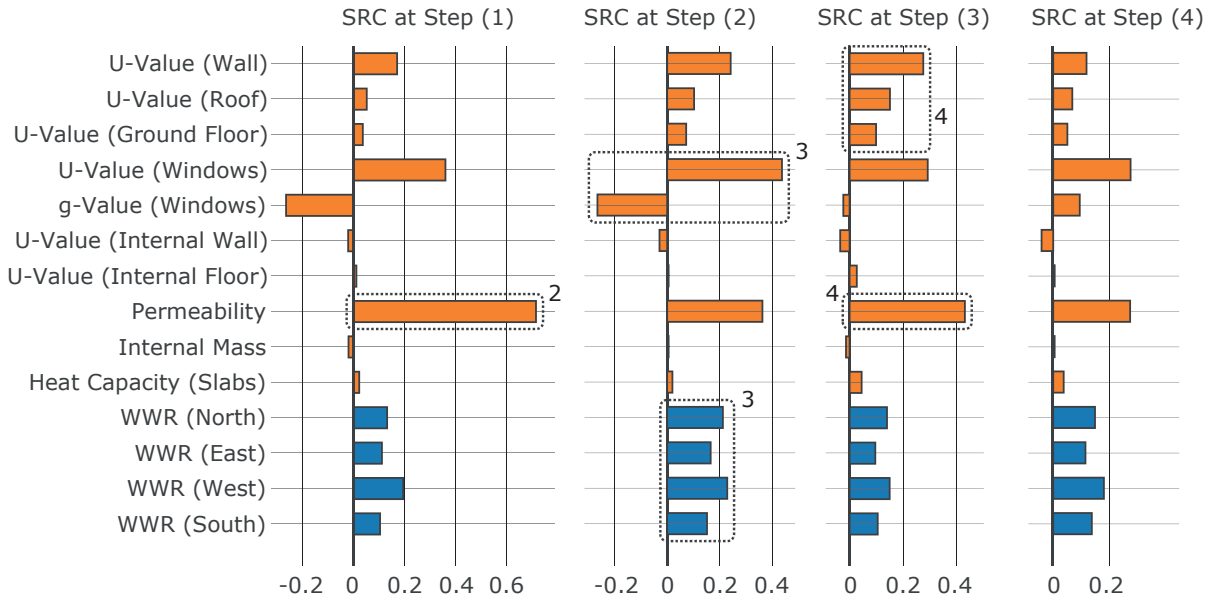

Figure 6.15 Change in parameter sensitivities from step (1) to Step (4)

For example, at step (1), permeability is the most influencing factor; hence, to move to step (2), the user reduces the range of permeability from (6.0 - 9.0) to (6.0 - 7.0). At step (2), sensitivity analysis results reveal that window parameters are important; hence, to advance to step (3), the user changes the ranges of U-value (window), g-value, and WWRs. The positive value of SRC suggests choosing a lower range for the parameters. For example, the g-value has a negative value of SRC; a higher range of (0.5 – 0.6) has been chosen. In the final step, the U-values of walls, ground floors, roofs, and permeability have been adjusted. Parameters with very small SRC such as U-value (internal floor and internal wall) and heat capacity have not been adjusted. Through these four steps, the user has improved the energy performance from 59.5±0.38 to 54.6±0.21kWh/m^2a.

3.1.3 Comparing design options

In this step, the user compares design options based on the predicted probabilistic EUI. The similar approach of creating design options and detailing steps, explained in the previous subsection, is used to create four design options. Table 6.5 and Figure 6.16 show the developed design options. These four design options differ from each other based on the mass model and window-to-wall ratios. However, technical specifications are identical for each design option. A probabilistic energy prediction is performed using 200 samples for each option. The results are presented using the box plots, as shown in Figure 6.16. The pair-wise comparison of p-values shows no difference (ND) for Op. (3) and Op. (4), only. For the remaining pairs, it is possible to make a clear distinction between the two designs. The overall analysis suggests that Op. (2) performs better than other options. In these comparisons, the predicted energy use is the lowest for the compact shape, Op. (2). However, Op. (1) which is more compact than Op. (3), has a higher energy use. The probabilistic parameters for these two options are different from each other.

Table 6.5 Probabilistic parameters for the design options

Parameter	Unit	Op. (1)	Op. (2)	Op. (3)	Op. (4)
U-value (Wall)	W/m^2K	0.16-0.18	0.16-0.18	0.16-0.18	0.16-0.18
U-value (Ground Floor)		0.16-0.18	0.16-0.18	0.16-0.18	0.16-0.18
U-value (Roof)		0.16-0.18	0.16-0.18	0.16-0.18	0.16-0.18
U-value (Window)		0.75-0.85	0.75-0.85	0.75-0.85	0.75-0.85
g-value	-	0.5-0.6	0.5-0.6	0.5-0.6	0.5-0.6
Air Permeability	$m^3/h \cdot m^2$	6.0-6.6	6.0-6.6	6.0-6.6	6.0-6.6
WWR (north)	-	**0.4-0.6**	**0.3-0.5**	**0.3-0.5**	**0.2-0.4**
WWR (east)		**0.7-0.9**	**0.7-0.9**	**0.3-0.5**	**0.2-0.4**
WWR (west)		**0.4-0.6**	**0.7-0.9**	**0.6-0.8**	**0.2-0.4**
WWR (south)		**0.7-0.9**	**0.7-0.9**	**0.6-0.8**	**0.7-0.9**
EUI (95% CI)	kWh/m^2a	55.0±0.21	54.0±0.23	54.6±0.21	54.7±0.22

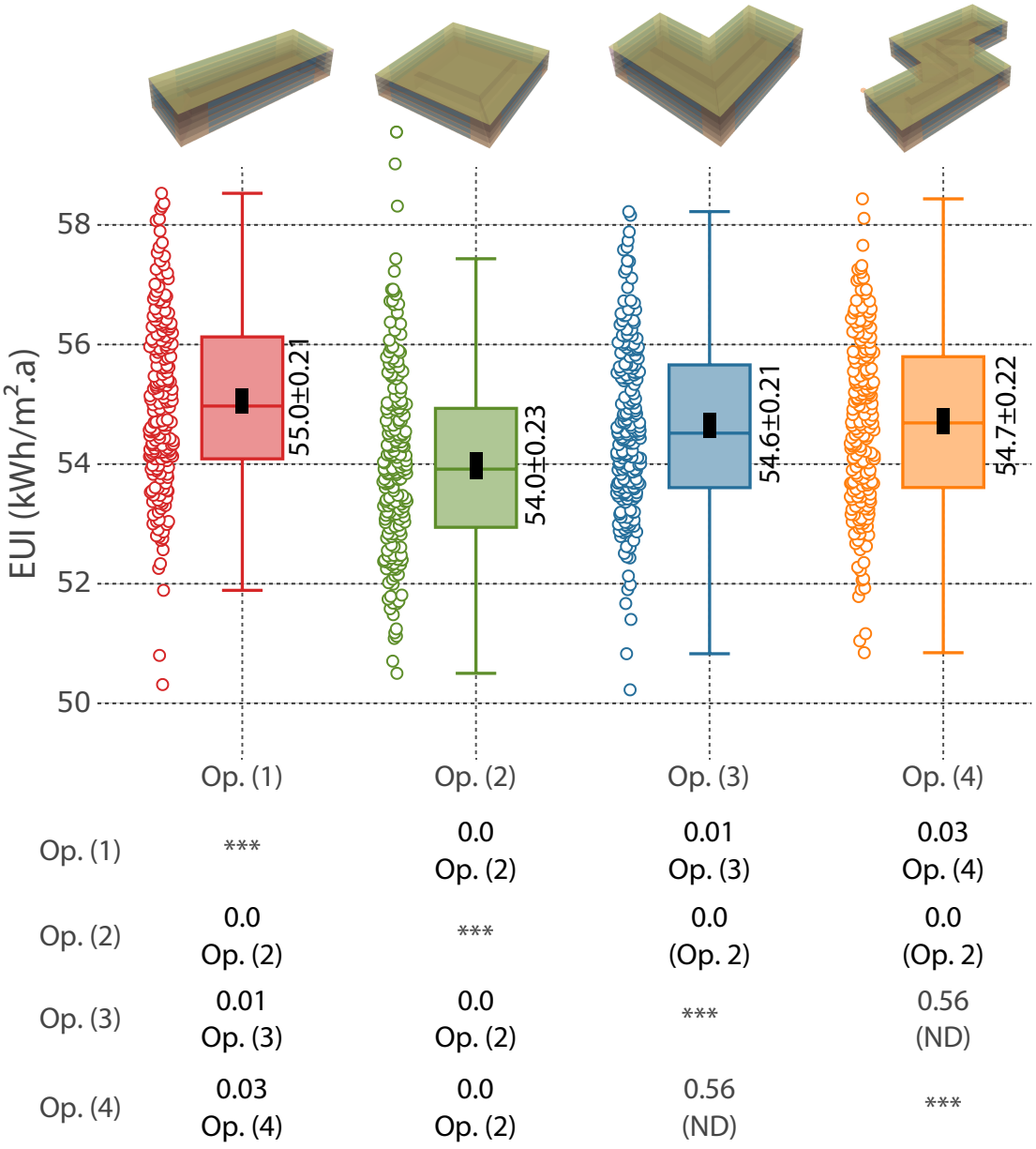

Figure 6.16 Comparing design options under uncertainty

3.1.4 Accuracy of ML predictions for the design case

The tool predicted the energy demand for 4400 samples in this design exercise. 1200 samples are evaluated for the design space and 800 samples for each option at four design steps. Dynamic simulations have been carried out using EnergyPlus to test the accuracy of ML predictions and compare the computational requirements. The results are presented in Table 6.6 and Figure 6.17. The figure presents errors in individual predictions using scatter plots and histograms. It clearly shows that the time required for ML predictions is far less than the simulation time. However, there is a slight loss in the accuracy. While design space samples record an error of 3.45 kWh/m2a (RMSE), Op. (1) samples have an error of 0.62 kWh/m2a

only. The ML model underpredicts most samples' energy demand, which results in the error of 4.17% (MAPE) and 2.78 kWh/m^{2}a (RMSE). The ML predictions are more accurate for Op. (1) than others, as suggested by the performance measures.

Table 6.6 Number of energy predictions and time required for different features

Building	Samples (Numbers)	Simulation Time (Seconds)	ML Time (Seconds)	ML Prediction Accuracy	
				MAPE (%)	RMSE (kWh/m^{2}a)
Design space	1200	15658	64	4.98	3.45
Op. (1)	800	8971	49	0.86	0.62
Op. (2)	800	7068	46	5.20	2.94
Op. (3)	800	13043	75	5.12	2.97
Op. (4)	800	13670	82	4.30	2.57
Overall	4400	58410	316	4.17	2.78

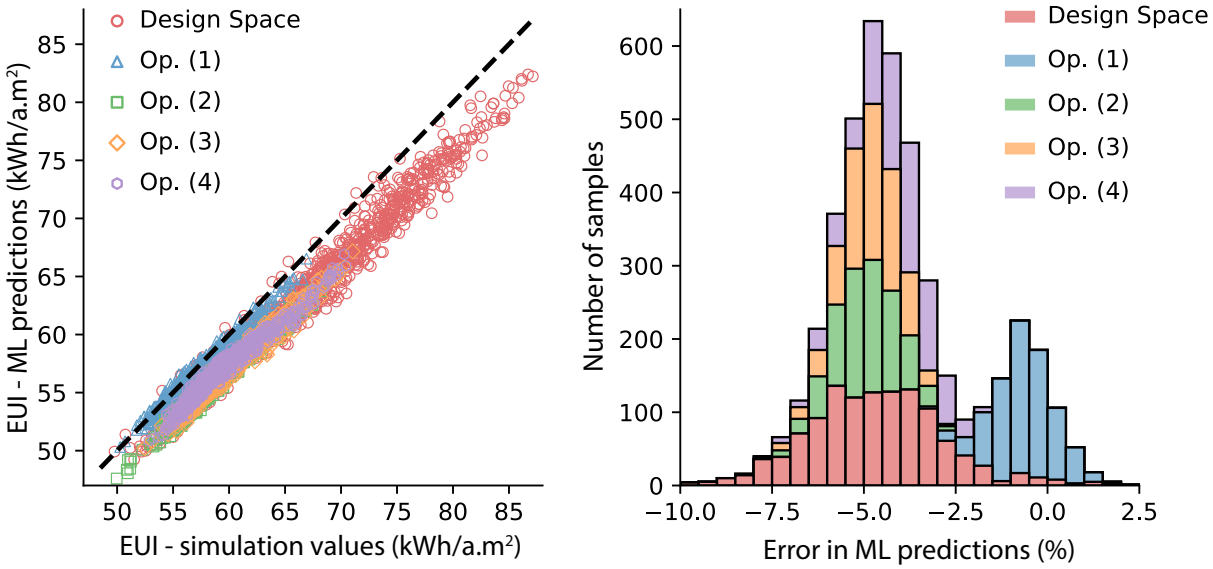

Figure 6.17 Accuracy of ML energy prediction for the design exercise

3.2 Feedback of the researchers

The subsection discusses feedback of 21 users to understand the functionality and limitations of the tool. It includes both quantitative and qualitative responses. The quantitative response assesses the level of information, time required for analysis, and ease of interpreting the information. Such feedback is not collected for tracking changes feature as it is primarily intended to manage changes rather than perform analysis. Besides these questions, feedback is collected to assess the tool's effect on creativity. A Likert scale of 1 to 5 has been used to collect this information, as shown in Figure 6.18. Further, the users have been asked detailed questions about their expectations, suggestions to improve the tool, and their way of interpreting information and using different features.

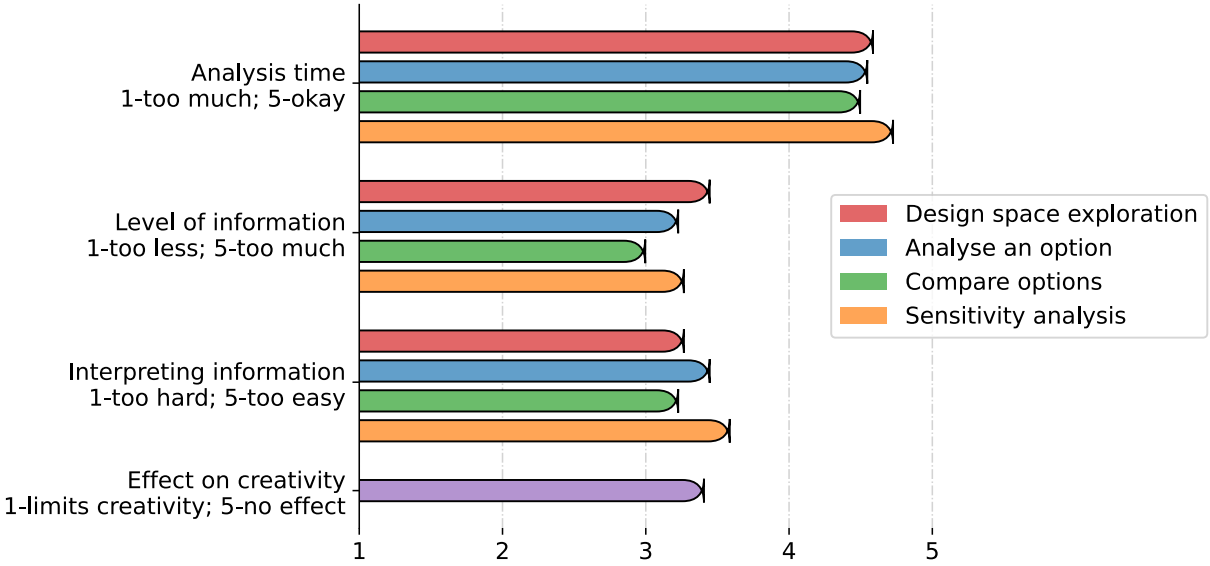

Figure 6.18 Quantitative feedback of the users

3.2.1 Is the time required to provide the analysis results reasonable?

The ML prediction is the most time-consuming task in the analysis. The ML predictions are performed several times for design space exploration to collect samples satisfying EUI and parametric constraints. EUI prediction for a design option requires 200 samples. On average, ML predictions for design space samples took around 90 seconds and for design option samples around 20 seconds. The users provided their feedback on a Likert scale of 1 to 5, where 1 represents too much time, and 5 represent okay. The users rated the tool 4.6/5 based on its time efficiency, suggesting that the time required for analysis is aligned to the requirements of the early stages.

3.2.2 Is the information provided by the tool sufficient and easy to interpret?

These two questions require the user response, which may go to either extreme, i.e., information is too much or too less, or it is too hard or too easy to interpret. Hence, we used a Likert scale of 1 to 5, representing the extreme responses. An ideal tool will have a rating of 3/5, suggesting that neither the information is too much or too less. Most users agree that the information is sufficient for all the features; it is neither too less nor too much. The users rated 3.2/5 for the level of information and 3.4/5 for ease of interpreting the information. Thus, it suggests that the users are not overloaded with the information. However, some users expected a better interpretation of box plots and sensitivity values.

3.2.3 Whether the tool limits the users' creativity?

The users rated the effect on creativity as 3.4/5, where 1 represents the tool limits creativity, and 5 represents no effect. Eight users agreed that the tool does not affect their creativity. However, five users were critical about the loss of creativity due to the automated generation of building shapes during design space exploration. Some users suggested incorporating more

features to control the building geometry of design space samples. The users appreciated that it allowed them to change the building geometry using the BIM tool and run energy analysis. However, a few users find it challenging to modify the mass model using Revit. This challenge is associated with the mass modelling process in Revit and a lack of experience; it does not reflect the complexity or limitation of the tool.

3.2.4 What features should be incorporated in the future?

The users have been asked to provide descriptive feedback through text. This feedback aims to identify the tool's shortcomings and additional features to improve its functionality.

Qualitative definition of technical specifications: A qualitative definition of the technical specification is required from an architect's perspective. The feedback suggests that instead of using a numerical value for U-value or permeability, an architect should be allowed to select building envelope using qualitative parameters, such as low U-value walls and high airtightness or low U-value windows with a high solar gain.

Geometrical flexibility: Due to limitations of the developed ML model, the tool only supports buildings with flat roofs, without courtyards, and the same floor plan for all levels. The users are advised to exclude any unsupported feature in their designs that severely affects their creativity. The tool does not propose to adapt the model as it is difficult to emulate unsupported geometrical features within the current limitations. The users suggested including sloped roofs, courtyards, non-rectilinear floor plans, and pre-defined shapes with flexible dimensions in future developments to improve the functionality.

Passive design strategies: The tool makes a few assumptions to predict EUI using the ML model. Such as, it does not consider the effect of window location and geometry, external shading, and shading from the surroundings. The users have suggested including these effects to achieve more realistic energy predictions. Moreover, the users are also interested in assessing the effect of other energy systems such as night ventilation, chilled beam/slab system, movable shading devices, and onsite energy generation systems. However, the tool does not support such analysis due to the limitations of the ML models.

Other suggestions: A few users suggested including textual suggestions or links to other references which can be used to understand the meaning of design parameters, distribution, regression coefficients, box plots, confidence intervals, and p-value. Some users with a background in lifecycle energy assessment have suggested more performance measures such as carbon footprint and global warming potential besides the EUI.

4. Discussion

The article developed a tool for probabilistic energy analysis combining ML and BIM. The tool provides energy information through five features: design space exploration, analysing an option, comparing options, sensitivity analysis, and track changes. The ML model is used to

quickly predict EUI, and BIM integration reduces remodelling efforts. The combination of ML and BIM provides quick and updated energy performance feedback. Once a user changes the design space or option, its effect reflects in the feedback. A test case of an office building is used to understand using the tool in a typical design process. Further, the article collects the feedback of 21 users to understand the usefulness and shortcomings of the tool.

The tool addresses the three challenges of early stage energy predictions – uncertainty, computational time, and modelling efforts by making probabilistic energy predictions using ML and BIM integration. However, implementing these approaches require a novel solution as previous solutions focussed on deterministic predictions using energy simulation tools. Further, it poses other challenges to glean meaningful information using statistical tools and its interpretation for making design decisions.

Probabilistic energy analysis of a design option is performed by predicting EUI for several combinations of uncertain parameters. The probabilistic results are presented using the mean value of predictions, 95% confidence interval, and a box plot. A box plot shows the minimum and maximum values and first and third quartiles. These statistical concepts need to be understood by the users for making design decisions. While the users with research background can easily interpret this information, it required additional efforts from the practising architects.

Further, uncertainty in the parameters requires sensitivity values to make design decisions, i.e., adjusting parameters. The article used standardised regression coefficients calculated using a linear regression model. The model based estimation of sensitivity indices is susceptible to the model's goodness-of-fit. However, this information is suppressed as it is of little use. Moreover, the number of samples used to estimate the confidence interval or compare design options is suggested to be 200. This number is based on the previous study, which used a similar parameter distribution. However, the article does not conduct any analysis to validate the number of samples as it will require more analysis in the background.

Interestingly, the track changes feature, which allows the user to navigate through the design decisions, has not been used by many users. One primary reason is that it does not perform any analysis and merely reproduces the energy predictions of a design option along the time axis. The limited functionality can be extended to make it more relevant for understanding the design changes.

The difference in the accuracy of ML predictions on the test dataset (Figure 6.3) and the design exercise samples (Figure 6.17) needs careful analysis. While the test dataset samples are collected for a wide range of design parameters, the samples of the design exercise represent its smaller subset. Thus, the error of the test dataset samples is merely an indication; and the errors can be less or more for specific design. However, it is not viable to check this difference while using the tool for a design exercise. Geometric and other limitations of the ML model

reduce the tool's utility. The ML model requires buildings with the same floor plan at each level, without a courtyard, flat roofs, and no external shading in its current version. The practising architects severely criticised these limitations. However, developing ML models for such a wide variety of buildings is a subject of further research. ML models are highly data-dependent models, i.e., their accuracy outside training cases is lower. The accuracy of ML prediction outside training cases is referred to as generalisation and is a broader research topic. The ML model generalisation is complex for early stage building configurations involving non-parameterised geometrical changes. Several research works have addressed this complex problem by developing component based ML structures [47], convolutional neural networks [198], and collecting new training samples [199]. [42,48] have developed a well-generalising ML model using transfer learning techniques to cover the test cases outside the parameter space. While these works claim a well-generalising ML model outside training data, it requires testing ML models to ensure their applicability on specific cases.

The tool allows updating the geometrical information using the BIM tool (Revit) and generating mass models in the BIM tool. It achieves the integration by writing the geometrical information in an open-source file format that is exchanged between the web tool and the BIM tool. As the information exchange is planned based on the known structure of the ML model and only one BIM tool, there were no interoperability issues. Moreover, the information contains only lists of points and some numeric information. The tool assumes a few constraints while creating options to allow energy prediction using the ML model. It will be interesting to develop a similar integration using industry foundation classes (IFC) with a more complex definition of building geometry.

5. Conclusions

The article developed a tool to provide energy-related information to support early stage design decisions by combining machine learning and building information modelling. A typical design process demonstrates its potential to provide useful information. The feedback of researchers and practising architects corroborates that the tool provides information to support energy-related design decisions. The information on design space exploration and analysis and comparing options allows evaluating several designs and provides their comparative assessment in a specific design context. Specific information is more reliable than the generic rules of thumb or conventional knowledge. After making design changes, the changes in sensitivity values underscores the need for such specific information. The advantage of using a machine learning model is reduced computational time. Since replacing dynamic simulation with a machine learning model causes only a small error of around 5%, it presents a promising prospect for future developments. However, other limitations of machine learning models need to be addressed through research to improve their usefulness in real design projects. The integration with the building information modelling tool allows reusing the geometric information for energy predictions, minimising the energy modelling efforts.

The article identified useful information that supports the design decisions and developed a technical framework to interactively provide the information. The developed tool allows experimenting with potential designs and improving their performances based on the energy performance information. Furthermore, the users' feedback provides insights into the usefulness of provided information and future requirements. Users' feedbacks underline the need to develop generalisable and robust machine learning models to predict energy performance of the early stage design configurations.

Acknowledgements
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************* *(end of the published article)* *************

Annexure E. Annexure to Chapter 6

The annexure discusses findings of the published article within the doctoral research context. The chapter focusses on the subobjective:

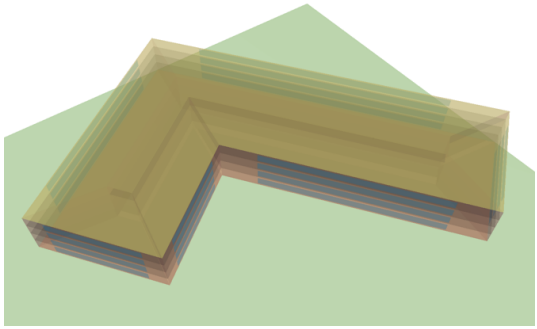
- To develop a design support tool that supports early stage design intervention by providing holistic and context-specific energy performance information.

The chapter developed a design support tool and tested its efficacy on a design case and by collecting users' feedback. It implemented the machine learning (ML) models in the web tool (p-energyanalysis.de) that interacts with the building information modelling (BIM) tool to provide quick context-specific feedback. The developed tool performs quick energy predictions and extracts useful information to support energy-related design interventions at the early stages. The tool provides information for design space exploration, analyse and compare design options, sensitivity analysis, and tracks changes. Designers are not restricted to automatically generated samples and are allowed to create a building option of their choice. However, restrictions in developing design options are imposed due to limitations of the ML model. The tool provides feedback that is updated for the design changes.

Question that can be answered by the developed methods

The chapter developed methods to support energy related design decision at the early stages. It used the ML model to reduce computational time and BIM to facilitate reusing design information for quick energy prediction. Further, it used statistical methods to extract useful information from probabilistic energy predictions for decision-making. The developed methods can answer the following energy related questions. We assumed a design option to elucidate the questions and their answers. The design option has a floor area of 1968 m^2, distributed equally over four levels. The floor-to-floor height is 3.3 m. Table 6.7 shows its 3D view and describes the design parameters.

Table 6.7 Description of Option 1

3D view of the design option	Parameter	Unit	Min	Max
	U-value (Wall)	W/m^2K	0.15	0.25
	U-value (Ground Floor)		0.20	0.20
	U-value (Roof)		0.15	0.25
	U-value (Window)		0.85	0.95
	g-value	-	0.4	0.5
	Air Permeability	$m^3/h{\cdot}m^2$	6.0	7.2
	Heat Capacity (Slab)	kJ/m^3K	0.6	1.0
	Internal Mass	kJ/m^2	15	45
	WWR (north and south)	-	0.5	0.7
	WWR (east and west)		0.3	0.5

It is assumed that the design parameters follow a uniform distribution suggesting that the designer can choose any value between the minimum and maximum value. The parameters mentioned in Table 6.8 are considered outside of design scope. It means these parameters will remain uncertain and follow uniform distribution with the mean value as the target and standard deviation (SD) representing variations due to several factors. Based on the above information about the design option, the developed methods provide the following answers about making a design change to the option:

Table 6.8 Uncertain parameters for analysing Option 1

Parameter	Unit	Mean	SD
Operating Hours	h	11	0.2
Occupancy	m^2/Person	20	0.5
Light Heat Load	W/m^2	7	0.5
Equipment Heat Load		12	0.5
Heating COP	-	3.0	0.1
Cooling COP		4.0	0.1
Boiler Efficiency		0.95	0.01

Q 1. What are the characteristics of the top 5 samples for Option 1?

Ans. The question relates to analysing random samples to identify the characteristics of low EUI buildings. Based on 200 random samples, 5 samples with the lowest EUI are mentioned in Table 6.9.

Table 6.9 Characteristic of the five samples with the lowest EUI

EUI / Parameter	Unit	Values				
EUI	kWh/m^2a	55.18	55.27	55.38	55.90	56.03
U-value (Wall)	W/m^2K	0.17	0.17	0.15	0.18	0.18
U-value (Ground Floor)		0.20	0.20	0.20	0.20	0.20
U-value (Roof)		0.15	0.20	0.18	0.17	0.20
U-value (Window)		0.86	0.86	0.89	0.87	0.85
g-value	-	0.43	0.49	0.50	0.50	0.48
Air Permeability	$m^3/h \cdot m^2$	6.26	6.17	6.04	6.16	6.40
Heat Capacity (Slab)	kJ/m^3K	0.6	1.0	0.8	0.8	0.9
Internal Mass	kJ/m^2	33	16	34	40	36
WWR (north)	-	0.53	0.52	0.61	0.52	0.60
WWR (east)		0.35	0.43	0.33	0.42	0.35
WWR (west)		0.40	0.38	0.37	0.43	0.37
WWR (south)		0.61	0.67	0.52	0.56	0.65

The information suggests that the five lowest EUI samples have **low U-values (less than 0.2 for solid components and less than 0.89 W/m^{2}K for windows)** and **low permeability (6.0 – 6.4 m^3/h.m^2).** The g-value of windows is around the maximum value of 0.5. The WWR in north and south direction is between 0.52-0.65 and in east and west is between 0.33-0.43. Heat capacity of floor slabs and internal mass almost reaches both the extremes. Hence, their effect can be ignored at this stage.

Q 2. What will be the change in the EUI of Option 1 if I increase floor-to-floor height from 3.3 m. to 3.6 m.?

Ans. The question requires assessing the effect of change in geometry of a design option. It will require modifying the building geometry using Revit. The user creates two variants of Option 1 i.e., V1 and V2 with the floor-to-floor height of 3.3 and 3.6 m, respectively. The tool estimates EUI of each variant using 200 random samples. It concludes that V1 has an EUI of 59.8 ± 0.24 and V2 has an EUI of 62.9 ± 0.29 kWh/a.m² (95% CI). **Hence, changing floor-to-floor height from 3.3 to 3.6 m. will increase the average EUI of Option 1 by 3.1 kWh/a.m² or 5.2%.** Similarly, a user can analyse the effect of other geometrical modifications that involve shape or dimensional changes.

Q 3. What will be the change in the EUI of Option 1 if I change the U-value of ground floor from 0.2 to 0.3 W/m^{2}K?

Ans. The answer assesses the effect of a deterministic parameter on the EUI. Since the U-value of ground floors is denoted parametrically, the user modifies the parameters using the web interface. **This parametric change increases EUI of the design option from 59.8 ± 0.24 to 60.4 ± 0.23 or by 1%.**

Q 4. What will be the change in the EUI of Option 1 if I change the U-value of walls from 0.2 ± 0.05 to 0.25 ± 0.05 W/m^{2}K?

Ans. The question requires assessing the effect of change in the mean value of a probabilistic parameter. The tool suggests that **this change increases the EUI from 59.8 ± 0.24 to 60.5 ± 0.25 kWh/m^{2}a or by 1.2%.**

Q 5. What will be the change in the EUI of Option 1 if I change the air permeability from 6.6 ± 0.6 to 6.6 ± 0.3 W/m^{2}K?

Ans. The question requires assessing the effect of change in the range of a probabilistic parameter. The tool suggests that **it does not affect the mean value of EUI; but reduces the 95% CI from ± 0.24 to 0.22 kWh/m^{2}a or by 8%.**

Q 6. What will be the change in the EUI of Option 1 if I change the U-value of walls from 0.2 ± 0.05 to 0.18 ± 0.01 W/m^{2}K?

Ans. The question requires assessing the effect of change in the mean value and range of a probabilistic parameter. The tool suggests that **the EUI changes from 59.8 ± 0.24 to 59.5 ± 0.24 kWh/m^{2}a after this parametric change.**

Q 7. What will be the change in the EUI of Option 1 if I reduce the U-value of windows from 0.9 ± 0.05 to 1.0 ± 0.05 W/m^{2}K and increase the window-to-wall ratio (west and east) from 0.4 ± 0.1 to 0.8 ± 0.1?

Ans. The question assesses the effect of changing two related probabilistic parameters. The tool suggest it will cause the EUI to increase from 59.8 ± 0.24 to 64.9 ± 0.29 kWh/m^{2}a or by 8.5%.

Q 8. What will be the change in the EUI of Option 1 if I reduce the U-value of windows from 0.9 ± 0.05 to 0.8 ± 0.05 W/m^{2}K and increase the air permeability from 6.6 ± 0.6 to 7.2 ± 0.6 m^3/h·m^2?

Ans. This question assesses the effect of changing two unrelated probabilistic parameters. The change in one parameter affect the effect of other parameters; however, the U-value of windows and air permeability are not related to each other. **The tool suggest it will cause the EUI to increase from 59.8 ± 0.24 to 59.9 ± 0.23 kWh/a.m². It means that the effect of increasing air permeability is compensated by reducing the U-value of windows.**

Question that can be answered by the developed methods

The developed method cannot answer the following questions. The limitations of the developed methods and methods to overcome these limitations have been also discussed.

Q 1. What will be the change in the EUI of Option 1 if I reduce the U-value of windows from 0.9 ± 0.05 to 0.75 ± 0.15 W/m^{2}K?

Ans. The tool will not accept this parametric change, as the ML model is trained and tested only in the range of 0.75 to 1.05 W/m^{2}K for the U-value of windows. It is possible for ML models to extrapolate; however, the performance of ML models needs to be tested for the new range. Moreover, if the ML model shows less prediction accuracy, it will require collecting new samples and retraining the ML model. Since this change just requires extending the range of a parameter, the new samples can be collected using the methods developed in Chapter 2.

Q 2. What will be the effect of using night ventilation, onsite-power generation, chilled beam/slab system, under floor heating, or movable shading on the EUI of Option 1?

Ans. All these changes reflect a non-parametric change to an energy model. The tool is developed to evaluate only parametric changes and non-parametric geometrical changes. All these changes are of similar nature and the following text explains these changes for the context of night ventilation. Assessing the effect of night ventilation requires a non-

parametric change to an energy model. The ML models, developed in Chapter 3 and Chapter 4, do not capture the effect of using night ventilation. First, it will require collecting training samples using dynamic simulations (EnergyPlus). Training dataset should have both samples i.e., with night ventilation and without it. Second, it will require developing an ML model structure that captures the effect of non-parametric variations. A component based approach discussed in Chapter 3 can capture non-parametric variation using components. Another approach can be a parametric ML model with a Boolean parameter to represent night ventilation. Both approaches to train ML model are possible to include the effect of such non-parametric variations. It is possible to develop ML models to capture the effect of onsite-power generation, chilled beam/slab system, under floor heating, or movable shading using the same approach. The method of integrating ML models with the BIM tool is not affected. However, it will require changing the web interface to handle the non-parametric or Boolean inputs.

Q 3. What will be the change in EUI if the user changes the geometry of the to one of the geometries shown in Figure 6.19?

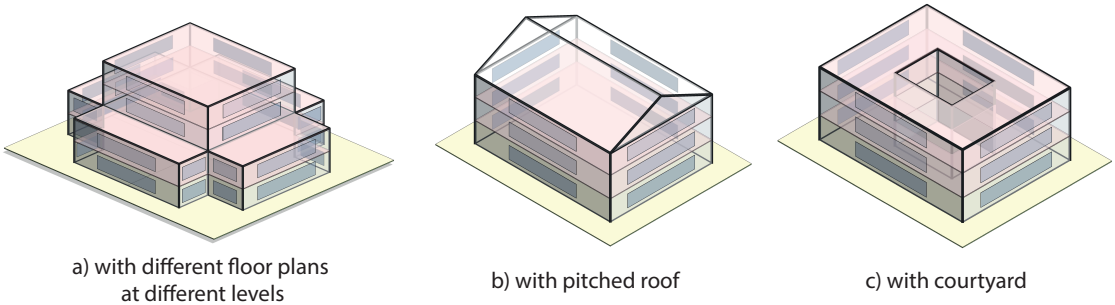


Figure 6.19 Geometrical changes to the design option

Ans. The tool cannot assess the effect of making the above geometrical changes to Option 1. Both, the developed ML models and integration with the BIM tool will require adaptations. Chapter 2 develops ML model using component approach and Chapter 3 using convolutional neural network. Both, ML structures can capture the geometrical variations, shown in the figure. The most time-consuming step in this development will be collecting new training samples. It requires several building energy models of different geometries to capture the effect of geometry. The current method of BIM integration needs to be updated, also. It should allow transfer the three-dimensional geometrical information from the BIM model to the web interface as opposed to current exchange of two-dimensional geometrical information.

Conclusions with respect to doctoral research objectives

The chapter developed a cloud based design support tool that quickly provides energy-related information. It uses the developed machine learning models from Chapter 4 and statistical methods to compare design options from Chapter 5. It developed an interface to allow users to

analyse the designed options and potential design solutions. It also provides context-specific sensitivity values that are more relevant than the traditional engineering knowledge. Above all, the tool provides all the information in an integrated environment that provides the user with various information to make design decisions. Users are allowed to experiment with different design cases and parameters and assess the context-specific effects of design decisions. At the technological level, the platform-independent development of the tool enables its wider accessibility and easy integration into the design process. Except for updating from the building information modelling tool, all features are accessible using the web interface. The test case and feedback of independent users conclude that the provided information is useful for designing energy-efficient buildings. Excluding a few limitations of the machine learning models, the tool efficiently provides energy related information to make decisions at the early stages.

7

Conclusions and future research

Chapter 7.
Conclusions and future research

The current approaches of building performance simulation (BPS) are inefficient to play an active role in supporting design decisions at the early stages. Uncertainty, high computational time, and expensive modelling efforts are prime challenges to early stage energy predictions that limits its use in decision-making at the early stages. All these challenges relate to the flexible nature of early design stages, which is vital to improve building performance, efficiently. Hence, the doctoral research aims to provide energy performance information to support energy-related design interventions while protecting the flexible nature of early design stages. The objective of the thesis is rephrased as follows:

> *"To provide quick, updated, and relevant information to support energy-related design decision under uncertain conditions of the early stages."*

The doctoral research addressed uncertainty using sensitivity analysis and statistical methods and high computational time by substituting dynamic simulations by machine learning (ML) models. Building information modelling (BIM) integrated approach is developed to minimise expensive modelling efforts. All the methods developed in the research are focused on achieving its primary objective of developing a design support tool. The thesis has been divided into five chapters, each focusing on specific research question to be answered to achieve its subobjective. The following sections reiterate the research questions and provides the conclusion to which extent the subobjectives are achieved and what are the limitations of the developed methods:

1. Subobjective 1: Information requirements for early stage energy prediction

Th subobjective of developing engineering knowledge to define information requirements at each level of multi-level-of-development (multi-LOD) by answering the following question:

? What is the uncertainty contribution of design parameters and parameter groups in the uncertainty of the predicted energy demand at an early design stage?

The second chapter used a medium-size office building test case to estimate the uncertainty contribution of design parameters at the early stages. The chapter considered different building geometries to include the effect of evolving building mass at the early stages. Sensitivity values are calculated using the variance based sensitivity analysis method to capture the complex parameter interactions of building energy models (BEM). By analysing changes in the variance of model outcome with different values of design parameters, the method calculates the first order and total effects. The first-order effect is a measure of uncertainty that can be removed by fixing the value of a design parameter. The sensitivity values suggested that the geometrical parameters cause more than 40% of uncertainty. It has been found that the variance of predicted energy reduces by more than 40% after removing the uncertainty in the geometrical parameters. Hence, the first-order sensitivity values are used to calculate the uncertainty contribution of the parameter groups.

The uncertainty contribution results suggested three identifiable levels used as the basis to define information requirements at three levels of multi-LOD. These results conclude that initially, geometrical parameters need to be defined with ±10% uncertainty and technical specifications and window parameters with ±25%. While making the design progress, the designer should find the values of geometrical parameters at level 1, followed by technical specification at level 2, and window parameters at level 3. Following this strategy, the uncertainty in the energy prediction will reduce by more than 40% at level 1, about 20% at level 2, and about 10% at level 3. The remaining uncertainty is caused by the parameters outside the scope of design.

The limitations of these findings arise from to which extent the selected test case represents the early design stages. The presented test case does not study the effect of on-site energy generation and different heating and cooling systems. It also does not include the effect of strategies such as, night ventilation or flexible shadings. Their presence or absence will also influence the energy predictions; hence, uncertainty in the predictions. While it considered various design parameters related to the early stages, the list can be extended to make the case more generalisable by including parameters related to system design. Considering these additional parameters is likely to affect the uncertainty contribution. However, it is unlikely to affect the order of design parameters to be focussed on each level, provided that the uncertainty in these additional parameters is restricted to realistic values.

2. Subobjective 2: Development of ML models for early stage energy prediction

The objective of developing well-generalising ML models for early stage energy prediction by answering two questions; the first is:

? What is the effect of different training samples on the model generalisation?

The third chapter utilised the concept of large training datasets to improve generalisation and investigated data collection approaches – increment and enrichment – to identify more useful training samples for improving the model generalisation. Comparing generalisation errors and distribution analysis of training samples suggested that diverse training samples are more useful for improving the generalisation than similar training samples. The chapter developed a method to identify diverse samples based on non-parametric characteristic, i.e., building shape. The chapter assessed the diversity of training samples as the two investigated data collection approaches only differ based on the shape of building energy models used to collect samples. The diversity of training samples needs to be determined in the context of ML model development. For example, if the ML model is developed for different locations, the diversity of training samples needs to be assessed based on their ability to reflect different weather conditions.

The data collection approaches have been tested for a previously developed component based ML (CBML) model extended to predict building energy demand. The ML model trained on the largest enriched dataset has generalisation errors of 8.79 MWh/a (root-mean-square-error) and 7.7 (mean-absolute-percentage-error), which are significantly lower than the model trained on smaller datasets. Unfortunately, these errors are considerably higher for making energy predictions with a 'small' prediction gap, as discussed in Chapter 5. The chapter concluded that the samples must be collected from BEMs of different shapes for training ML models for early stage energy predictions.

The second question answered to achieve the subobjective of developing well-generalising ML models is:

? Which ML model structure captures the shape information better than parametric approaches to make energy predictions?

The fourth chapter proposed an ML model structure to train a well-generalising ML model for early stage energy predictions. The premise of proposing a new model structure was that a simple parametric representation of building shape is insufficient to capture its effect on the energy performance. The proposed ML model has a convolutional neural network (CNN) to process the shape information from an image of the building footprint. The findings concluded that the proposed ML model structure captures the effect of building shape on its energy performance and has a lower generalisation error than the previously developed ML model capturing the shape information by a parameter. The proposed ML model with CNN allowed developing model with very low generalisation error, i.e., 2.11 kWh/m^{2}a (root-mean-square-error) and 1.97% (mean-absolute-percentage-error). However, it has a limitation in that it cannot be used for the building with different floor plans at different levels.

The ML model development was limited to medium-size office buildings used as test cases. It considered a wide range of design parameters that are relevant for the early design stages. However, it only gives little importance to heating and cooling systems by representing them only with efficiency parameters. Similarly, training and test samples represent building operation by operating hours, fixed setpoints, number of occupants, and heat gains. These are valid assumptions considering the early design stages. The developed ML models cannot be used to evaluate strategies such as night ventilation and flexible shading. ML models need collecting new training and test samples and retraining if the energy systems, building operation, or other building characteristics are essential aspects of the early stages.

3. Subobjective 3: Effect of substituting simulations by ML models on decision-making

The fifth chapter assessed the suitability of ML based quick energy predictions for comparing design options at the early stages by answering the following question:

? What are the acceptable limits of error (prediction gap) for ML models that do not affect the comparative assessment of design options at the early stages?

The doctoral thesis used the connotation 'small' prediction gap to conclude that ML based energy predictions can substitute dynamic simulations at the early stages. The prediction gap is considered 'small' if it does not affect the decision-making under the uncertain scenario of the early design stages. Chapter 5 used a medium-sized office building test case to demonstrate the proposed methods of comparing design options under uncertainty. Different design options and an acceptable range of design parameters are considered to emulate early design stages. The chapter used the extended version of ML models developed in Chapter 3. The ML model shows an accuracy of 0.94 (R^2) and an error of 4.2 MWh/a (root-mean-square-error) on the test dataset. The findings concluded that ML based energy predictions are 50 times quicker and provide the same results as dynamic simulations for comparing design options. Hence, any ML model with a similar or better accuracy than this ML model may substitute dynamic simulations for comparing design options under uncertainty at the early stages.

The objective of using ML based energy predictions is to reduce the computational expensiveness of dynamic simulations to obtain probabilistic BPS results. Hence, the study also included other alternative approaches to reduce computational time – deterministic approach and simplified thermal zoning for dynamic simulations. Both approaches reduce the computational expensiveness; however, these approaches do not provide the same comparative assessment results as the state-of-the-art approach of probabilistic, detailed, and dynamic simulations. The developed ML model allows quick energy prediction and comparison of design options during the early design stages, making it a suitable candidate to replace dynamic simulations. However, their aptness must always be considered with their limitations. ML models are trained for specific design cases, such as the developed model can only be used for office buildings for the location of Munich. The ML model needs new training and test data

and retraining and testing for other location or building use. Further, the accuracy of ML predictions can only be guaranteed on the design cases that are similar to the test cases. Hence, the ML models cannot completely replace the dynamic simulations; however, in specific instances, ML models can be used to predict energy performance quickly and in decision-making. Further, developing the ML model requires additional time and expertise.

4. Subobjective 4: Development of ML and BIM based tool to support design decisions

The sixth chapter developed a tool to support early stage design decisions by providing quick, holistic, and context-specific energy performance information. It achieves its objective by exploring the following research question:

? Which information is relevant for making energy-related design interventions, and how will it be provided in short time?

The doctoral thesis identified four primary features (information) of the design support tool – design space exploration, analysing an option, sensitivity analysis, and comparing design options. An additional feature, track progress, does not perform any analysis. It provides information to visualise the changes in the energy performance and retract unwanted design changes. The chapter demonstrated how the provided information is used to make energy-related design interventions. It showed that sensitivity values of design parameters change with design changes underlining the need to provide updated information. Independent researchers and practitioners also tested the tool, and their feedback suggested that the provided information supports to change design and improve building performance.

The chapter also answers how to provide the information in short time. A straightforward solution is using ML based energy predictions. However, it must be noted that energy prediction results are merely data, and the tool must extract useful information. For design space exploration, the tool created samples satisfying the design criteria, followed by energy predictions. For analysing an option, the tool predicted the probabilistic energy performance and extracted information such as the mean value, confidence interval, and range of energy use intensity (EUI). The predicted energy performance is used for sensitivity analysis to calculate the regression based sensitivity index – standardised regression coefficient. Comparing design options determines whether two options have a significant difference in the energy performance using the Wilcoxon-rank sum test, concluding a better option between the two. Designers are provided with all this information to make design decisions.

On technological aspects, the tool is developed as a cloud based service that can interact with the BIM tool. By allowing the user to update the geometrical changes from BIM, it reduces the remodelling efforts. However, the designer needs to assign probabilistic design parameters in the web interface to experiment with building specifications easily. A library of possible

building specifications, such as medium insulation construction with a high window-to-wall ratio, can be developed to reuse these probabilistic parameters on different design projects.

A major limitation of the tool is associated with the ML model. The users' feedback suggested developing ML models that cover more architectural design possibilities such as internal courtyards, pitched roofs, and different floor plans at different levels. This limitation requires further research in ML development for early stage energy prediction. Further, there are some challenges in understanding the statistical terms for practising architects. Their feedback will help overcome the shortcomings of the design support tool through future developments.

5. General conclusions regarding challenges to early stage energy predictions

Three primary challenges, i.e., uncertainty, computational expensiveness, and expensive modelling efforts, are critical to early stage energy predictions; hence, making it difficult to obtain valuable information for decision-making. The thesis has developed methods to address these challenges and extract the information while keeping the flexible nature of early design stages. The following subsections summarise the thesis conclusions with respect to the challenges to early stage energy predictions:

5.1 Uncertainty at early design stages

The thesis concluded that the parameters need to be defined with reasonable or acceptable uncertainty limits at the beginning of the design. As design progresses, designers need to focus on some of the design parameters and reduce uncertainty by detailing. It is essential to define the building geometry, followed by technical specifications and window parameters. Since the design parameters are uncertain at the early stages, making precise energy predictions is neither advisable nor possible. However, the objective is to predict energy performance as realistic as possible by making suitable assumptions based on standards and available data. Probabilistic energy predictions are useful to address the uncertainty at the early stage. However, these results require sensitivity analysis and statistical methods to extract any useful information for decision-making. Sensitivity indices require updating to design changes to assess the effect of design parameters on energy performance (context-specific). Similarly, statistical methods are required to compare design options under uncertainty.

5.2 The computational expensiveness of dynamic simulations

Dynamic simulations are computationally expensive to perform probabilistic energy predictions. Hence, the thesis developed metamodels (engineering-surrogate model) using ML approaches. Developing an ML model is a challenging task for early stage energy predictions due to evolving building geometry. However, the two used approaches, component based ML (CBML) and convolutional neural network (CNN), allow training an ML model with low generalisation errors. The developed ML model is used to make quick energy predictions, compare design options, and develop a design support tool (Chapter 6). These developments conclude that the ML model is suitable to substitute dynamic simulation with some limitations.

5.3 Expensive modelling efforts

Developing energy models from the design information requires expensive modelling efforts. BIM is used as a facilitator to extract the geometrical information and provide input to ML models, minimising the remodelling efforts. Quick energy prediction for comparing design options (in Chapter 5) and developing a design support tool (in Chapter 6) uses BIM in the background to make geometrical changes. Extracting BIM information for any performance assessment is based on certain assumptions and modelling guidelines. These requirements are expressed implicitly in the thesis. Such as, a designer needs to create a building mass model and define probabilistic parameters to perform energy predictions. A designer needs to spend some additional effort to model according to these requirements. Hence, BIM reduces the remodelling efforts by reusing the modelled information across different disciplines. But it still requires modelling all the information relevant to making a performance assessment.

6. Outlook for future research

Machine learning and building information modelling offer promising prospects for developing novel solutions that will allow designing energy-efficient buildings from their conception, and the doctoral thesis tried to contribute to this endeavour. The thesis developed methods to overcome several challenges of early stage energy predictions and developed ML models and integrated with BIM solution for developing a design support tool. While the thesis presents a significant development to promote the use of ML based BPS results for supporting design interventions at the early stage, there is a long journey ahead before a tool can be realised for practical implementation. The research has pointed out major limitations related to developing an ML model for quick energy prediction. Hence, the following subsections provide advanced concepts to develop ML models and describes relevant concepts to improve the design support tool.

6.1 Component based approach for building energy systems

The thesis demonstrated that ML components can be trained to predict the energy performance of building elements (walls, floors, and roofs). These ML components learned the generalising behaviour of these elements from the data and were used to predict the energy performance of complex building shapes. The approach can be extended to predict the energy performance of different building systems. Automated shading, lighting control, chilled beam/slab, solar or wind electricity generation etc., are potential energy-saving systems requiring a high initial cost. Their effects on the energy performance needs to be known before recommending any system. Figure 7.1 shows a conceptual overview of CBML based development of energy prediction models for different building energy systems. An ML component representing the performance of a building energy system can be trained and used to predict energy demand. The ML components can be trained for systems such as automated shading, lighting control, under floor heating, and night ventilation. However, it requires engineering knowledge to define the model structure for CBML approach besides a huge amount of data.

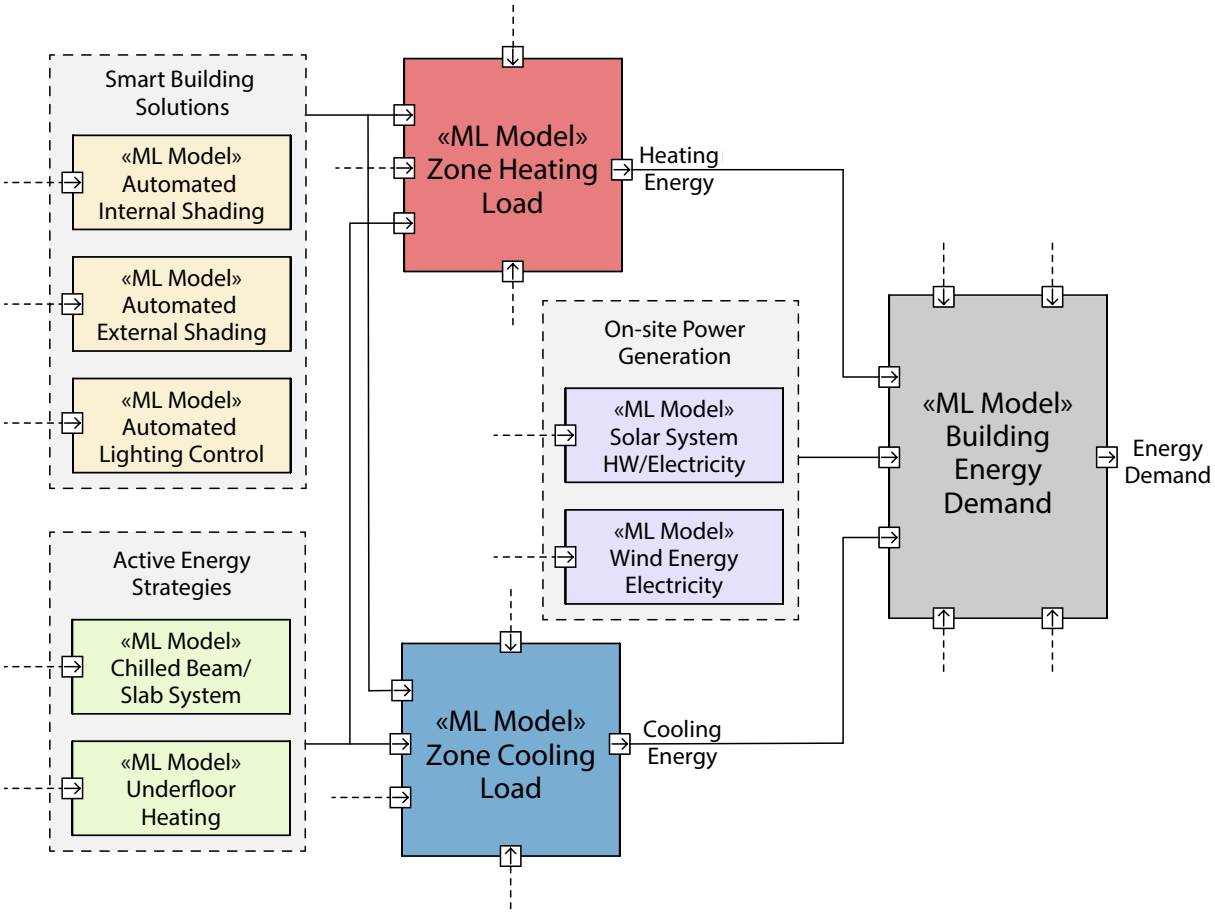


Figure 7.1 A conceptual overview of the CBML model for energy components

6.2 Three-dimensional CNN model for complex building shapes

The thesis concluded that an ML model with convolutional layers captures the effect of building shape on its energy performance. The developed monolithic ML model has very low generalisation errors by learning the effects of relevant features on energy predictions from the data. The approach requires that the relevant building features are well represented in the data and the ML model. The thesis trained the CNN model that uses two-dimensional (2D) images to capture the building shape information. This representation of building shape limits the model's ability to capture the shape information along the third axis, i.e., height. However, this limitation can be overcome by training a three-dimensional (3D) CNN model. Figure 7.2 shows the conceptual representation of a 3D CNN model. This model structure has convolutional layers to process the 3D shape information that is merged with other numerical parameters and connected to a fully connected neural network. The model can also process numerical parameters and its interaction with the building. The same structure can be extended to include Boolean parameters such as the presence or absence of energy saving strategies – flexible shading, night ventilation, or chilled beam/slab system.

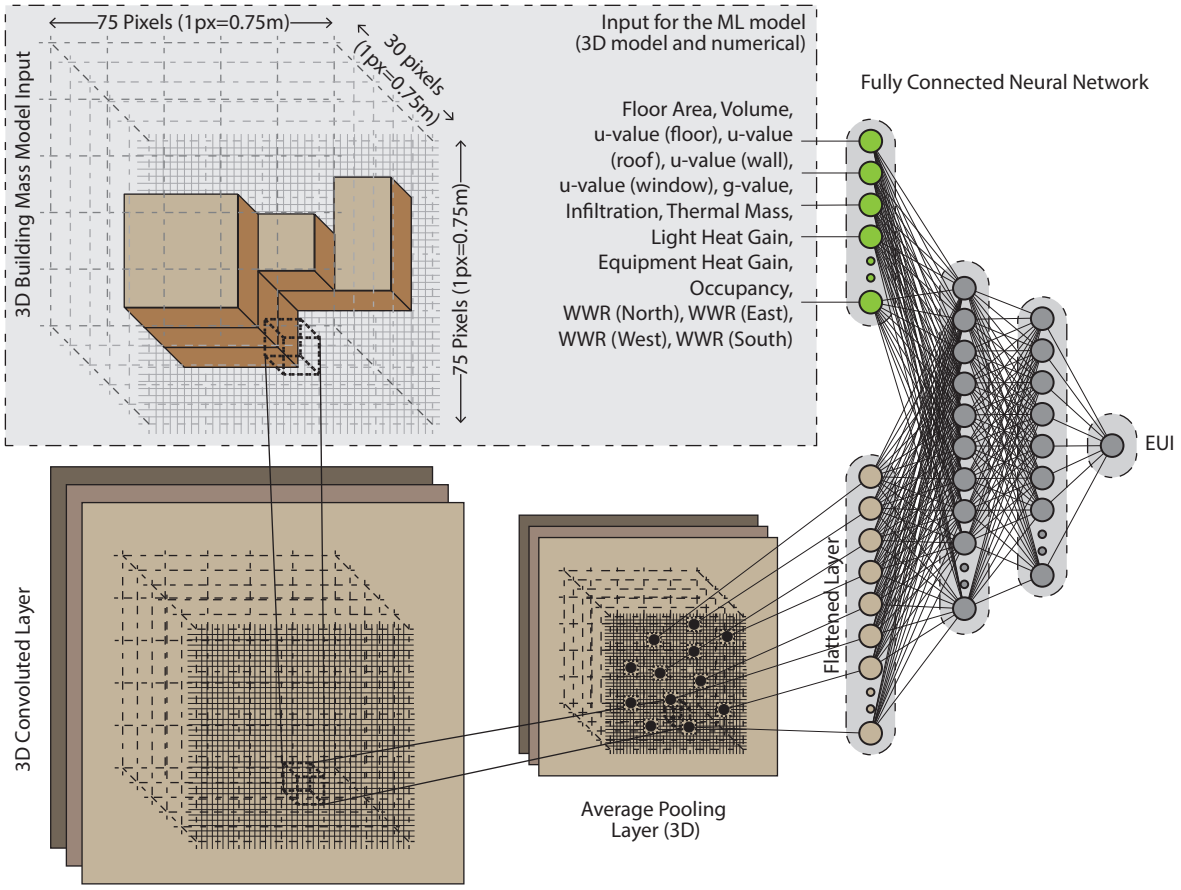


Figure 7.2 A conceptual representation of 3D CNN model

6.3 Other relevant concepts to improve design support tool

The following points discuss relevant concepts to improve the utility of design support tools:

1. The building design is a multi-disciplinary exercise. While the thesis considered energy an important criterion, designers need to make decisions based on several performance measures. A more holistic approach needs to be developed that can evaluate the design solution based on several performance measures, quickly.
2. BIM integrated approach is vital to developing any design support tool. While theoretically, BIM can provide all the relevant information for energy modelling, it is challenging to develop practical solutions. These challenges point towards the lack of standardised modelling guidelines. In most of the cases, performance assessment methods require to follow specific modelling guidelines.

"Research is a learning process and learning never ends."

- Dr Shrabani Saha

Appendix A.
Calibration of EnergyPlus Model (one-zone-per-floor approach)

We used a medium-sized office building Tausendpfund, in Regensburg near Munich, Germany to calibrate an EnergyPlus model. Only, heating and cooling energy data is available to calibrate the simulation results [89]. The following sections provide details of the building and the energy model:

Geometrical details of building energy model

The building has a box-shaped shape with the external dimensions of 14.7m × 27.0m × 9.75m. It has the same floor plan at each floor with a total area of around 1200 m^2. Around 725 m^2 (60%) space is used as an office and the remaining area accounts for walls, corridors, and service spaces. Based on the window-to-wall ratio of 0.33 in each direction, the energy model has a window of equivalent size in the middle of walls. To simplify generating thermal zones for different dimensions, we used one-zone-per-floor rule to create thermal zones, as shown in Figure A.1[86].

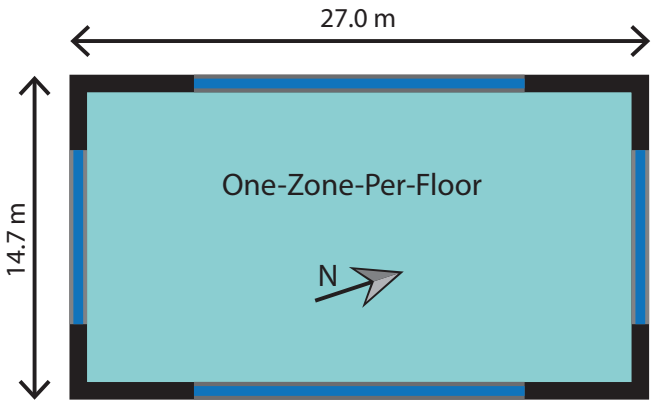


Figure A.1 Floor plan of Tausendpfund building

Calculated design parameters

We calculated the U-values, heat capacity of floor slabs, and infiltration based on the information available about the construction components:

U-values: The U-values of walls, ground floor and roof are calculated based on the thickness of each material layer and its thermal conductivity. For example, the external walls have four layers. An 18 cm. thick structural layer with the thermal conductivity of 2.3 W/mK, two 2 cm. thick finish layers with the thermal conductivity of 0.7 W/mK, and an 18 cm. thick insulation layer with the thermal conductivity of 0.035 W/mK. These properties give a U-value of 0.18 W/m^2K for walls. Windows have a transparent portion with the U-value of 0.6 W/m^2K and a solid portion with the U-value of 1.25 W/m^2K that gives an equivalent U-value of 0.87 W/m^2K for windows. Similarly, the transparent portion has a g-value of 0.6, and the overall g-value for windows is 0.35, considering 42% area as the frame.

Heat capacity (Slab): This parameter denotes the heat capacity of major structural components i.e., reinforced concrete floor slabs. The floors have 25 cm. thick slabs with a density of 2300 kg/m^3. It will result in an approximate heat capacity of 0.8 kJ/kg K.

Air tightness: The building is classified as Type-II construction as per the DIN-18599 standard that suggests the air permeability will be less than 6 m^3/h.m^2 for energy calculations [194]. The infiltration rate is calculated by (0.07×ρ×A/0.8×V + 0.1) air changes per hour (ACH), as illustrated in DIN-18599. 0.07 is volume flow coefficient (standard value as per DIN EN ISO 13789), ρ is air permeability, A is total surface area, V is the external volume, and 0.8 is a factor to calculate net volume from external volume. 0.1 is added to account for infiltration through windows [213]. Hence, the calculated infiltration rate is 0.3 ACH.

Heat pump and boiler: The building has a heat pump with the rated coefficients of performance (COP) of 2.8 (heating) and 3.6 (cooling). It has a boiler with an efficiency of 0.95 to provide additional heating. Heating and cooling are provided by supplying hot and cold water through an under-floor system. The energy model uses EnergyPlus objects 'HVACTemplate:Zone:WaterToAirHeatPump' connected to 'HVACTemplate:Plant:Boiler' to simulate the energy system.

Table A.1 Calculated design parameters

Parameters	Unit	Value	Parameters	Unit	Value
U-value (Wall)	W/m^{2}K	0.18	Heat Capacity (Slab)	kJ/kg K	0.8
U-value (Ground Floor)		0.19	Infiltration	ACH	0.3
U-value (Roof)		0.15	Heating COP	-	2.8
U-value (Window)		0.87	Cooling COP		3.6
g-value	-	0.35	Boiler Efficiency		0.95

Assumed design parameters

We made some reasonable assumptions regarding the building operation considering building is typically used as an office.

Setpoints: The heating and cooling setpoints are 20°C and 25°C, respectively. If building is used from 07:30AM to 06:30PM, the setpoints are used from 06:30AM to 06:30PM. The setback temperatures are 15°C (heating) and 30°C (cooling) for the remaining hours.

Ventilation: The ventilation rate is calculated based on the number of occupants which is simulated using an EnergyPlus object 'ZoneVentilation:DesignFlowRate'. We also assumed natural ventilation by opening windows as the temperature is more than 23°C but less than 25°C. The same EnergyPlus object is used to simulation natural ventilation with the parameters 'Ventilation Type' as 'Natural' with 2 ACH.

Building schedule: The building is assumed to follow a typical 5-day schedule without holidays. Typically, an office in Munich observes ten holidays in a year. The building is assumed to be in operation for 11 hours a day from 07:30 AM to 06:30 PM.

Calibrated design parameters

We calibrated design parameters related to internal mass and heat gains to match the simulated heating and cooling energy with the measured values.

Internal mass: This internal mass is considered to simulate the behaviour of internal partitions and furniture. A typical dry-wall construction using two Gypsum board gives a thermal mass of 75-90 kJ/m^{2}K. Similarly, the thermal mass of furniture in a medium-furnished office is around 15-45 kJ/m^{2}K. Hence, we have tried a value between 90-135 kJ/m^{2}K to account for internal mass of partitions and furniture.

Light heat gain: The building is installed with manually controlled LED lamps. Considering an illuminance requirement of 500 lux for office spaces, it will require 6-9 W/m^2 to provide the required illumination. The energy model considers dimming the artificial lights if the daylight is available. The light heat gain is reduced to 10% during the non-working hours, i.e., from 06:30 PM to 07:30 AM.

Equipment heat gain: Based on the typical office use and design, the equipment heat gain has an approximate value of 10-15 W/m^2. Same as the light heat gain, it is reduced to 10% during non-working hours.

Occupancy: Based on the design information, there is around 45-60 users during working hours. It converts to the occupancy rate of 20-27 m^2/person.

After making several trials, we calibrated design parameters, as mentioned in Table A.2.

Table A.2 Calibrated design parameters

Parameter	Unit	Min	Max	Calibrated Value
Internal Mass	kJ/m^{2}K	75	135	120
Light Heat Load	W/m^2	6	9	6
Equipment Heat Load		10	15	12
Occupant Load	m^2/Person	20	27	24

Comparison of simulated and actual energy consumption

Figure A.2 presents the simulated and actual energy consumption. Since we only have information about the actual heating and cooling energy requirements, we used the simulated heating and cooling energy requirements in this figure. The simulated energy consumption of the building is 43.98 MWh/a. Out of this 43.98 MWh/a, 35.86 MWh/a is required for heating

and 8.12 MWh/a for cooling. 37% of the heating requirement is met by the heat pump and remaining by the electric boiler.

In 2017, the energy requirement was 42.08 (36.4 heating + 5.7 cooling) MWh/a, around 4.28% less than the simulated value. In 2018, the energy requirement was 45.9 (36.2 heating + 9.7 cooling) MWh/a, around 4.34% more than the simulated value. Hence, the simulated energy requirement has a mean absolute error of 4.31%.

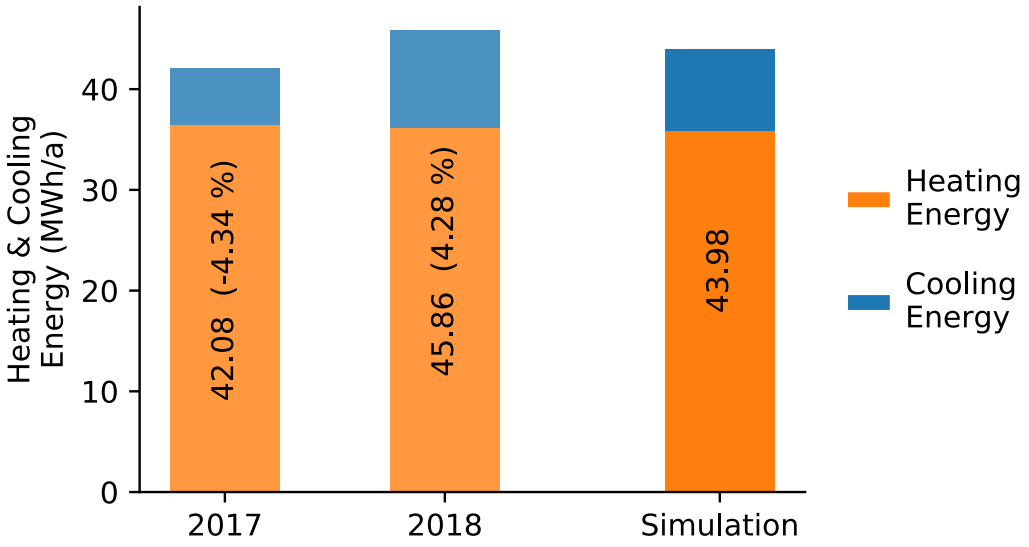


Figure A.2 Comparison of simulated and actual energy consumption

There is no data available for lighting energy consumption. The simulation data suggest an approximate energy requirement of 21.95 MWh/a, for lighting, which translates to an annual electrical consumption of 18.35 kWh/m^{2}a. In total, the building requires 65.93 MWh/a, for providing heating, cooling, and lighting which corresponds to annual energy consumption of 55.13 kWh/m^2.

Check for other shapes

This energy model is also used for other shapes which will have self-shading which reduces the incident solar radiation on the shaded wall surfaces. We used the coordinate representation all the building surfaces. For example, “BuildingSurface:Detailed” object is used to create walls, floors, roofs, and “FenestrationSurface:Detailed” is used to create windows. This representation calculates insolation values using EnergyPlus shadow algorithm. We checked the insolation values for two shapes – box and plus shape (shown in Figure A.3). As evident in this figure, the walls N1, N3, E1, E3, W1, W3, S1, and S3 receives self-shading while the wall N, E, W, S, N2, E2, W2, and S2 do not receive any shading.

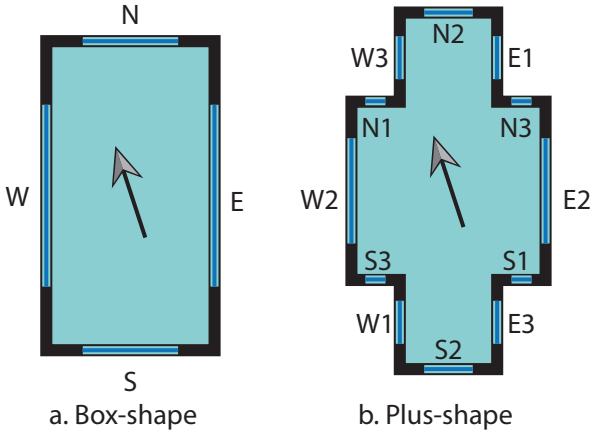


Figure A.3 Wall nomenclature for box and plus-shape building

Table A.3 compares the average annual insolation values for the ground floor walls of box and plus shape building. This comparison shows that walls that do not receive any self-shading has the highest insolation values for their respective direction while self-shaded walls have lower insolation values. While both the box and plus shape buildings have the same floor area, their energy requirements are significantly different (box - 43.97 MWh/a and plus shape - 59.86 MWh/a). This difference is caused by several factors that includes increased infiltration due to higher surface area-to-volume ratio and increased heat loss through walls and windows, besides self-shading.

Table A.3 Insolation values for the ground floor walls of box and plus shape building

Insolation (W/m^2) – Box	Insolation (W/m^2) – Plus Shape
N - 44.3	N1 - 33.6, N2 - 44.3, N3 - 29.7
E - 63.0	E1 - 42.4, E2 - 63.0, E3 - 56.4
W - 83.9	W1 - 73.7, W2 - 83.9, W3 - 62.7
S - 96.5	S1 - 63.4, S2 - 96.5, S3 - 65.3

EnergyPlus model used for calibration is available on Mendeley datasets [214].

Appendix B.
Calibration of EnergyPlus Model (core-and-perimeter-zone approach)

The calibration of multi-zone EnergyPlus model is performed using the same building as in Appendix A; however, adopting more detailed approach for creating internal zones. While the model in Appendix A uses one-zone-per-floor rule to generate thermal zones, this model uses core-and-perimeter-zone approach to create internal zones [173]. Figure B.1 shows the floor plan of thermal zones. This approach of creating zones, offsets each edge by a distance (4.5 m. in this case). It creates the same number of perimeter zones as the edges (four in this case) and one core zone. While creating the zones for complex shape (as shown in Appendix C), it has been ensured that the edge length is always more than the twice of offset distance. Hence, it will always result in one core zone and perimeter zones, corresponding to each edge.

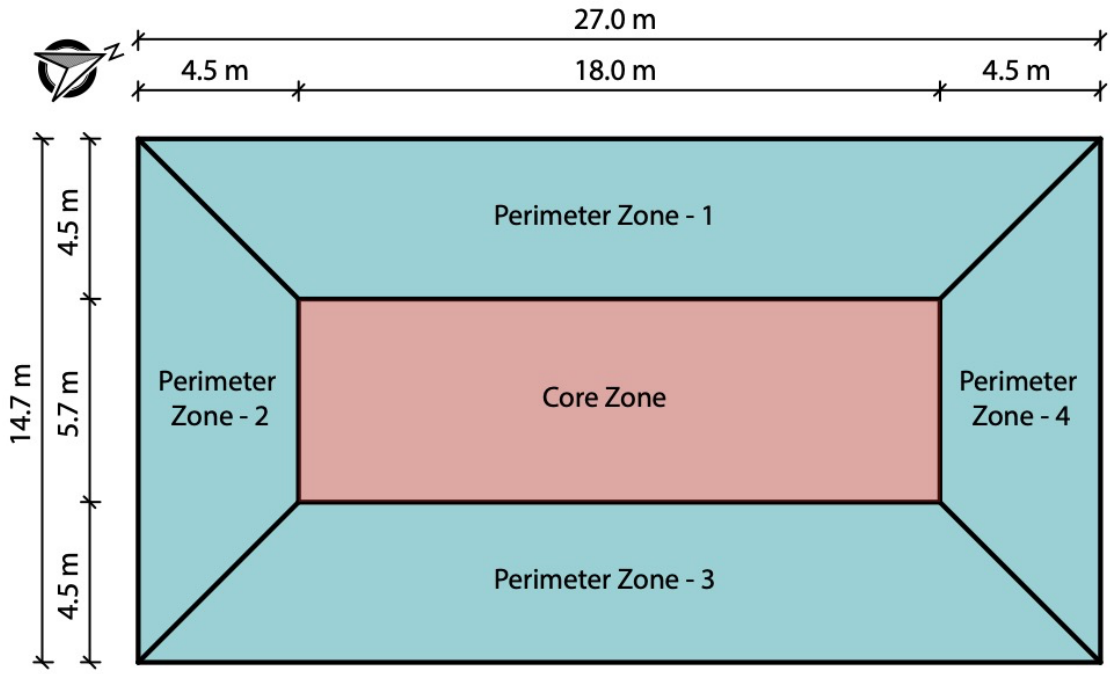


Figure B.1 Simplified thermal zone floor plan of Tausendpfund building

The values of all the calculated and assumed parameters remain the same as mentioned in Appendix A. The values of calibrated design parameters are mentioned in Table B.1. In this energy model internal mass only accounts for the furniture. Internal wall area created in the energy model.

Comparison of simulated and actual energy consumption

Figure B.2 presents the simulated and actual energy consumption. Since we only have information about the actual heating and cooling energy requirements, we used the simulated heating and cooling energy requirements in this figure. The simulated energy consumption of the building is 44.32 MWh/a. Out of this 44.32 MWh/a, 36.86 MWh/a is required for heating

and 7.46 MWh/a for cooling. 39% of the heating requirement is met by the heat pump and remaining by the electric boiler. In 2017, the energy requirement was 42.08 (36.4 heating + 5.7 cooling) MWh/a, around 5.07% less than the simulated value. In 2018, the energy requirement was 45.9 (36.2 heating + 9.7 cooling) MWh/a, around 3.48% more than the simulated value. Hence, the simulated energy requirement has a mean absolute error of 4.28%. While the error in predicting heating energy is around 1.5%, the error in predicting cooling energy is around 27%.

Table B.1 Calibrated design parameters

Parameter	Unit	Min	Max	Calibrated value
Internal Mass	kJ/m^{2}K	15	45	30
Light Heat Load	W/m^2	6	9	6
Equipment Heat Load		10	15	12.5
Occupant Load	m^2/Person	20	27	24

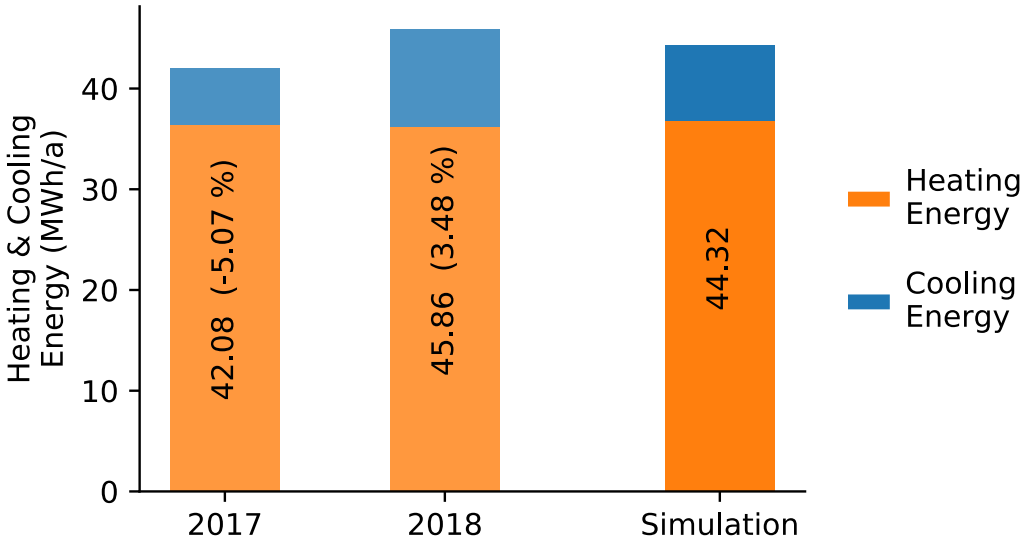


Figure B.2 Comparison of simulated and actual energy consumption

There is no data available for lighting energy consumption. The simulation data suggest an approximate energy requirement of 20.94 MWh/a, for lighting, which translates to an annual electrical consumption of 17.5 kWh/m^{2}a. In total, the building requires 65.26 MWh/a, for providing heating, cooling, and lighting which corresponds to annual energy consumption of 54.57 kWh/m^2. EnergyPlus model used for calibration is available on Mendeley datasets [215]

Appendix C. Algorithm to generate random floor plans

We assume the same floor plan at each level while generating a random floor plan. A floor plan is generated by arranging square boxes next to each other. It requires some inputs to determine constrain - boundary/site boundaries; size - floor area, number of floors, orientation; and complexity - maximum number of boxes (max_boxes), minimum (min_edge) and maximum (max_edge) edge size of the box. For example, increasing min_edge will generate more simpler shapes while reducing the values will allow more complex shapes. An example of generating a random floor plan is shown in Figure C.1. The tool uses the following algorithm used to generate a random floor plan:

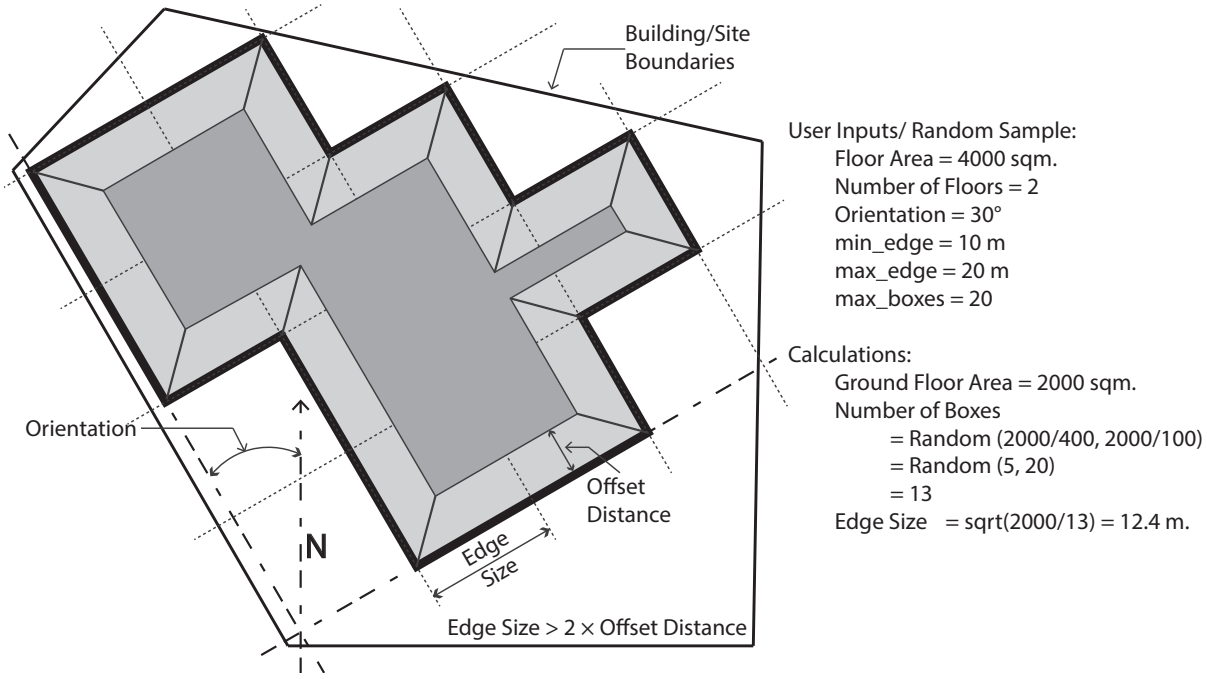


Figure C.1 Example of generating random floor plan

1. Ground Floor Area = Total Floor Area / Number of Floors; while Ground Floor Area < min_edge × min_edge, reduce Number of Floors by 1.
2. Number of boxes = random (ground floor area / max_edge^2, ground floor area / min_edge^2); if the number of boxes > max_boxes, then Number of boxes = max_boxes
3. Edge size = sqrt (Ground Floor Area / Number of Boxes)
4. Generate grid, equivalent to the edge size, on the site according to orientation.
5. Select boxes randomly on the grid (next to each other) to make a shape for floor plan.

The above algorithm is only exemplary to demonstrate generating random floor plans for creating energy model in Chapter 3 and Chapter 4. It is also used to generate the design space samples in Chapter 6. It is only used to create random samples when a user has not created the mass model and looking for possible designs. Users are allowed to control the geometry to many possible designs using Autodesk Revit.

Appendix D.
Principal component analysis for dimensionality reduction

Principal component analysis (PCA) is a statistical approach for identifying principal features based on the total variance [129]. It transforms the dataset to a new coordinate system such that the first axis of the new coordinate system captures the maximum variance, followed by the second and so on. Thus, the direction of the first axis refers to the first principal component [216]. It is useful in transforming a high dimensional dataset into a lower-dimensional dataset by extracting principal features along with principal components.

An example of transforming a two-dimensional dataset into a one-dimensional dataset using linear PCA is shown in Figure D.1. Part (a) shows a two-dimensional dataset that has two dimensions (features) x1 and x2 and ten data points. Based on these data points, principal components are calculated using singular value decomposition [217–219]. The two principal components for the given dataset are shown by the red and blue dashed lines. Intuitively, the direction of the 1st (red-dashed line) principal component represents the axis that maximises the variance of the dataset. As in this case, the ratio of variance explained by the 1st and 2nd principal components are 88% and 12%, respectively. As the original dataset has only two dimensions, two principal components will capture the entire variance. The dataset is shown in part (b) is rotated so that the direction of the principal components become axes of the cartesian plane. For reducing dimensionality, the data points are projected onto the principal components. Grey lines from a data point (×) on a red-dashed line show these projections. After the dimensionality reduction, the data points are represented by (·) that has only one dimension. The value represented by a (·) on the red dashed line is the first principal feature of the corresponding sample. For example, the sample (0) that is earlier represented by [0.79, 0.41] is represented by [-0.11] after the dimensionality reduction. However, the transformed dataset will have reduced variance, i.e., 88% of the original dataset.

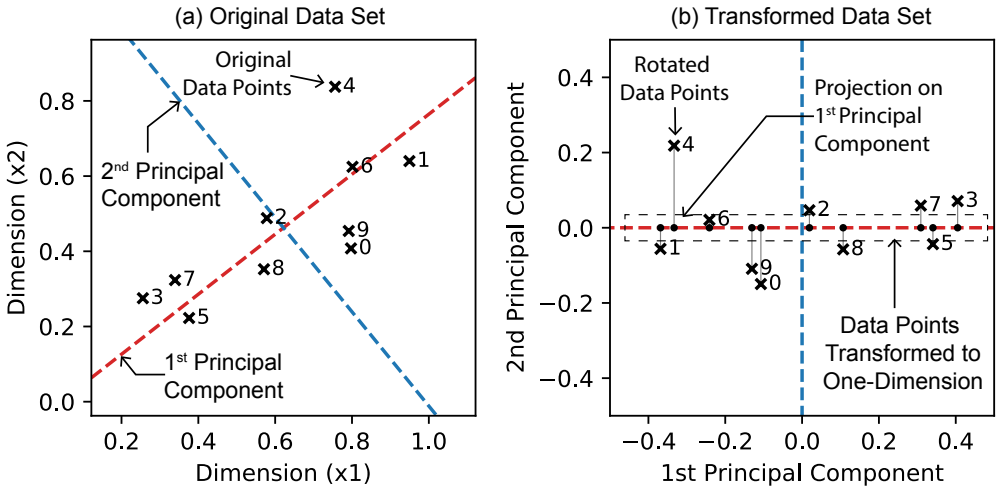


Figure D.1 Illustration of principal component analysis using two-dimensional data

A similar understanding of linear PCA can be extended to any n-dimensional dataset to reduce its dimensions to m, such that m ≤ n. Thus, PCA reduces dimensionality, increasing interpretability while minimising the loss of information [128]. There are more sophisticated techniques for dimensionality reduction, such as Kernel PCA [220], auto-encoders [221], and t-stochastic neighbour embedding [222]. However, linear PCA is a widely used and simpler dimensionality reduction technique for complex datasets [128]. Sonka, Hlavac, and Boyle describe the application of PCA for dimensionality reduction of images in detail [223]. Several researchers have used PCA to compress images by extracting important features. This method of image compression heavily relies on the ability of PCA to extract the most important features that allow image reconstruction [129,224]. PCA found its application to preprocess image data for machine learning models by extracting important features [225,226]. Hence, PCA reduces the dimensionality of images by extracting the most relevant features to improve their interpretability.

In this study, PCA is used for the dimensionality reduction of the samples represented by an image of 20×20 pixels. It reduces the dimensions from 400 (20×20) to two dimensions so that these samples can be visualised in a two-dimensional space. Figure D.2 shows ten selected shape samples. Black and white pixel have the value of 0 and 1, respectively, in this figure.

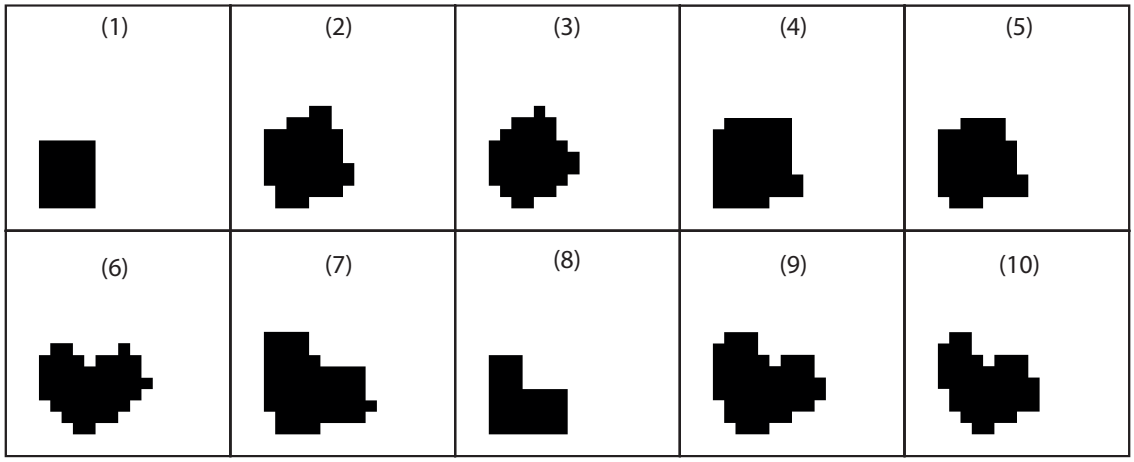


Figure D.2 Samples represented by its shape using 20×pixels black & white image

PCA is used to transform this image dataset by extracting two principal features. Figure D.3 shows the transformation matrix that is used to extract the principal features. The extracted feature is the weighted sum of a pixel value of the sample (shown in Figure D.2) and the value corresponding to its location in the matrix (shown in Figure D.3). Thus, a higher value (or black pixel) in the transformation matrix suggests that a specific feature focuses on a specific region of the sample. Figure D.3 highlights the regions focussed by the first and second principal features using black-dashed lines. It suggests that the first principal feature analyses the value of a pixel in the region bounded by a black-dashed line, as shown in Figure D.3 (a). Similarly, the second principal feature focuses on other regions, as shown in Figure D.3 (b).

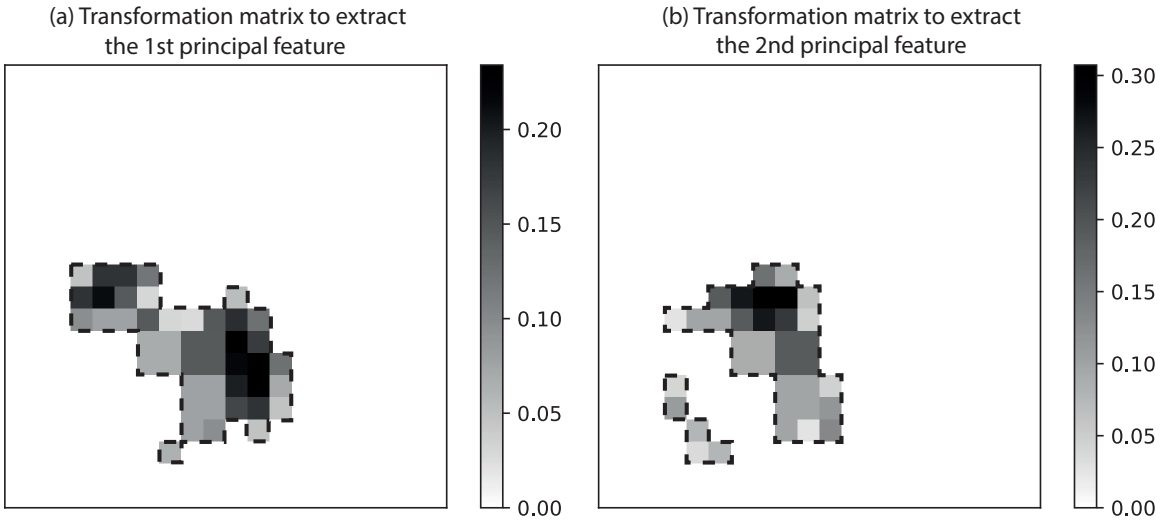


Figure D.3 20×20 transformation matrix used to extract principal features

Appendix E. Developing machine learning models using CBML

The appendix develops machine learning (ML) model for implementation purpose in Chapter 5. It uses component based machine learning model (CBML) approach, proposed by [47] and developed further in Chapter 3. We retrained the ML model and tested its accuracy on a combination of random building shapes, shown in Figure E.1 and design parameters, mentioned in Table E.1. It requires to retrain the ML model as there are differences in parameters' ranges from Chapter 3. Further, the ML model is required for implementation purpose while Chapter 3 only demonstrates the method to improve the generalisation. Based on the sampled value of the total floor area, a random building shape is generated for the sample using the algorithm mentioned in Appendix C. The randomness of building shapes and design parameters ensures the applicability of ML models on similar building configurations of the early stages. We used the EnergyPlus model, calibrated in Appendix B, to collect training and test data.

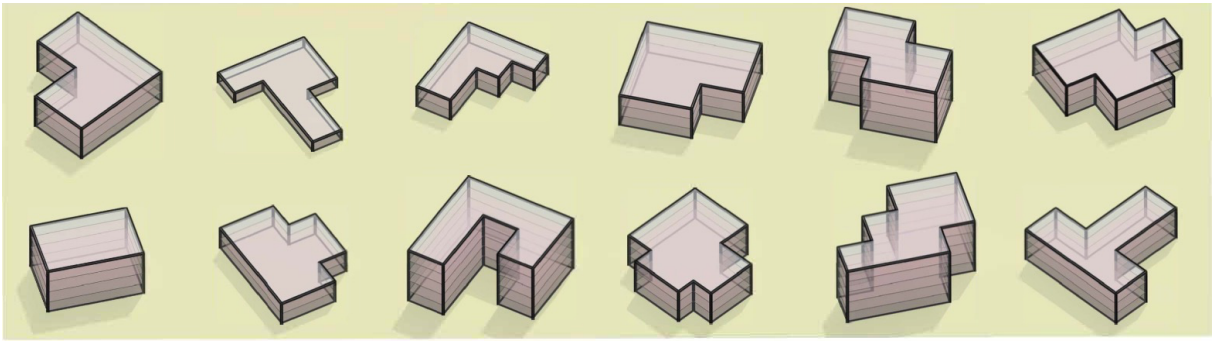


Figure E.1 Random building shapes used to test the accuracy of ML predictions

Table E.1 Details of design parameters to test the accuracy of ML predictions

Parameter	Unit	Range	Parameter	Unit	Range
Total Floor Area	m^2	(400, 2000)	Internal Mass	kJ/m^2	(15, 45)
Floor-to-Floor Height	m	(3, 4)	WWR	-	(0.2, 0.8)
No. of Floors	-	(2, 4)	Heating COP	-	(2.5, 3.5)
Orientation	degrees	(0, 45)	Cooling COP		(3.5, 4.5)
U-value (wall)	W/m^2 K	(0.1, 0.3)	Boiler Efficiency		(0.86, 0.98)
U-value (ground floor)		(0.1, 0.3)	Light Heat Gain	W/m^2	(3, 9)
U-value (roof)		(0.1, 0.3)	Equipment Heat Gain		(8, 16)
U-value (window)		(0.6, 1.2)	Occupancy	m^2/Person	(15, 25)
g-value	-	(0.15, 0.65)	Operating Hours	Hours	(8, 14)
Infiltration	ACH	(0.15, 0.45)			

3000 samples are generated using Sobol sampling [111] for training and 1000 samples are generated using Latin hypercube sampling [110] for testing the ML model. The energy demand includes energy required to provide heating, cooling, and lighting. The ML model predicts the

total annual building energy demand in MWh/a. CBML model has the similar structure as mentioned in Chapter 3, except an additional model at zone level to predict the lighting energy demand. The CBML has total 8 ML components that have been trained, individually, on the simulation data. The same strategy, used in Chapter 3, have been used for hyperparameter tuning and restrict overfitting. The best model based on the least validation loss is used to report the accuracy of ML model. The accuracy of ML predictions is presented using a scatter plot in Figure E.2. The ML model shows an accuracy of 0.94 in terms of R^2, root mean square error (RMSE) of 4.2 MWh/a, and mean absolute percentage error (MAPE) of 4.89%. Figure E.2 shows that many test samples are close to the black-dashed line, suggesting that the prediction errors are small. The histogram suggests that all the test samples have less than of 10% error and around 70% samples have less than 5% error.

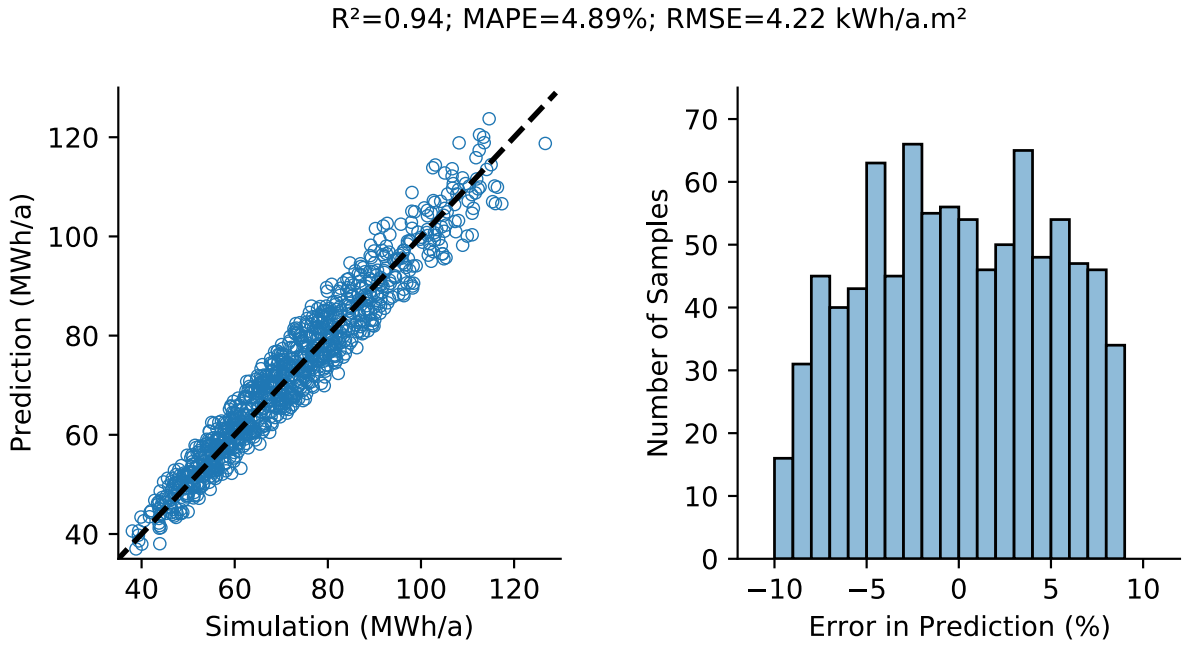


Figure E.2 Accuracy of ML prediction with reference to EP simulation

The developed ML model is limited to the simulation data which is used to generate the training and test datasets. Thus, the results must be interpreted within the context of EnergyPlus simulation model, mentioned in Appendix B and parameters' ranges, mentioned in the appendix. The ML model are only applicable within the constraints of the energy model such as location, building use, ventilation and lighting requirements, and schedules, etc. The data used for testing ML model is available on Mendeley datasets [227].

Appendix F. Developing machine learning models using CNN

The appendix develops a machine learning (ML) approach proposed by [198] for implementation purpose in Chapter 6. The proposed approach uses the image of the building floor plan and numerical parameters (technical specifications) as inputs to predict the energy demand. The image input is processed using a convolutional neural network (CNN) and merged with a deep neural network to process it with numerical parameters. More details about the model architecture are provided in the reference [198]. Based on the previous studies, we selected the parameters' ranges, as mentioned in Table F.1 [22,25,103]. These parameters are assumed to be continuous between the defined min and max values. These ranges are only exemplary to demonstrate the proposed approach. We generated 25000 samples using Sobol sequences for the training dataset and 1000 samples for the test dataset. The energy demand includes energy required to provide heating, cooling, and lighting.

Table F.1 Details and range of design parameters used in this study

Parameter	Unit	Range	Parameter	Unit	Range
Floor area	m^2	(1000, 5000)	Internal Mass	kJ/m^2	(15, 45)
Number of floors	-	(1, 6)	WWR	-	(0.05, 0.95)
Height	m	(3.0, 4.2)	Operating Hours	h	(8, 14)
Rotation	degrees	(0, 90)	Occupancy	m^2/Person	(15, 25)
U-value (Wall)	W/m^2K	(0.15, 0.35)	Light Heat Load	W/m^2	(4, 10)
U-value (Ground Floor)		(0.15, 0.35)	Equipment Heat Load		(8, 16)
U-value (Roof)		(0.15, 0.35)	Heating Setpoint	°C	(19, 21)
U-value (Window)		(0.75, 1.05)	Cooling Setpoint		(25, 27)
g-value	-	(0.3, 0.6)	Heating COP	-	(2.5, 4.5)
Air Permeability	$m^3/h{\cdot}m^2$	(3, 9)	Cooling COP		(2.5, 4.5)
Heat Capacity (Slab)	kJ/m^3K	(0.6, 1)	Boiler Efficiency		(0.90, 0.98)

An ML model is trained using the same method as described in Chapter 4. Sixteen combinations of hyperparameters have been tried and the best model is selected based on the least validation error. The developed model shows a mean-absolute-percentage-error of 1.80% and a root-mean-squared-error of 4.17 MWh/a. The details of the ML model to generalise are described in Chapter 6. The developed ML model is limited to the simulation data which is used to generate the training and test datasets. Thus, the results must be interpreted within the context of EnergyPlus simulation model, mentioned in Appendix B and parameters' ranges, mentioned in the appendix. The ML model are only applicable within the constraints of the energy model such as location, building use, ventilation and lighting requirements, and schedules, etc. The data used for developing ML model is available on Mendeley datasets [228].

References

[1] European Environmental Bureau (EEB), A blueprint to deliver a healthy, affordable, and sustainable built environment, Brussels, Belgium, 2021. https://eeb.org/wp-content/uploads/2021/03/Blueprint-for-sustainable-built-environment.pdf

[2] J. Clarke, Energy simulation in building design, 2nd ed.; 2, Butterworth-Heinemann, 2001. https://www.sciencedirect.com/book/9780750650823

[3] R.F. Rupp, N.G. Vásquez, R. Lamberts, A review of human thermal comfort in the built environment, Energy Build. 105 (2015) 178–205. https://doi.org/10.1016/j.enbuild.2015.07.047

[4] European Commission, The Energy Performance of Buildings Directive, 2019. https://ec.europa.eu/energy/sites/default/files/documents/buildings_performance_factsheet.pdf

[5] L. Pérez-Lombard, J. Ortiz, C. Pout, A review on buildings energy consumption information, Energy Build. 40 (2008) 394–398. https://doi.org/10.1016/j.enbuild.2007.03.007

[6] European Commission, Energy use in buildings, (2021) (accessed December 25, 2021). https://ec.europa.eu/energy/eu-buildings-factsheets-topics-tree/energy-use-buildings_en

[7] European Commission, Comprehensive study of building energy renovation activities and the uptake of nearly zero-energy buildings in the EU, 2020. https://ec.europa.eu/energy/sites/ener/files/documents/1.final_report.pdf

[8] A. Kaklauskas, R. Gudauskas, Intelligent decision-support systems and the Internet of Things for the smart built environment, in: Start-Up Creat., Elsevier, 2016: pp. 413–449. https://doi.org/10.1016/B978-0-08-100546-0.00017-0

[9] J. Parasonis, A. Keizikas, A. Endriukaitytė, D. Kalibatienė, Architectural Solutions to Increase the Energy Efficiency of Buildings, J. Civ. Eng. Manag. 18 (2012) 71–80. https://doi.org/10.3846/13923730.2011.652983

[10] A. Sawhney, J.U. Maheswari, Design Coordination Using Cloud-based Smart Building Element Models, Int. J. Comput. Inf. Syst. Ind. Manag. Appl. 5 (2013) 445–453. http://www.mirlabs.org/ijcisim/regular_papers_2013/Paper120.pdf

[11] Royal Institute of British Architects (RIBA), BIM Overlay to the RIBA Outline Plan of Work, 2012. www.ribaplanofwork.com

[12] Building and Construction Authority, Singapore BIM Guide - Version 2.0, Singapore, 2013. https://www.corenet.gov.sg/media/586132/Singapore-BIM-Guide_V2.pdf

[13] J. Hester, J. Gregory, R. Kirchain, Sequential early-design guidance for residential single-family buildings using a probabilistic metamodel of energy consumption, Energy Build. 134 (2017) 202–211. https://doi.org/10.1016/j.enbuild.2016.10.047

[14] P.B. Purup, S. Petersen, Requirement analysis for building performance simulation tools conformed to fit design practice, Autom. Constr. 116 (2020) 103226. https://doi.org/10.1016/j.autcon.2020.103226

[15] A. Yaneva, Scaling Up and Down, Soc. Stud. Sci. 35 (2005) 867–894.

https://doi.org/10.1177/0306312705053053

[16] S. Ammon, Why Designing Is Not Experimenting: Design Methods, Epistemic Praxis and Strategies of Knowledge Acquisition in Architecture, Philos. Technol. 30 (2017) 495–520. https://doi.org/10.1007/s13347-017-0256-4

[17] J. Abualdenien, A. Borrmann, Multi-LOD model for describing uncertainty and checking requirements in different design stages, in: Proc. 12th Eur. Conf. Prod. Process Model., Copenhagen, Denmark, 2018. https://www.researchgate.net/publication/327836788

[18] S. Attia, E. Gratia, A. De Herde, J.L.M. Hensen, Simulation-based decision support tool for early stages of zero-energy building design, Energy Build. 49 (2012) 2–15. https://doi.org/10.1016/j.enbuild.2012.01.028

[19] J. Abualdenien, P. Schneider-Marin, A. Zahedi, H. Harter, H. Exner, D. Steiner, M. Mahan Singh, A. Borrmann, W. Lang, F. Petzold, M. König, P. Geyer, M. Schnellenbach-Held, Consistent management and evaluation of building models in the early design stages, J. Inf. Technol. Constr. 25 (2020) 212–232. https://doi.org/10.36680/j.itcon.2020.013

[20] P. de Wilde, Building Performance Analysis, First, John Wiley & Sons, Ltd, Chichester, UK, 2018. https://doi.org/10.1002/9781119341901

[21] Energy Star, What is Energy Use Intensity (EUI)?, (2021). https://www.energystar.gov/buildings/benchmark/understand_metrics/what_eui

[22] Federal Ministry of Transport Building and Urban Affairs (BMVBS), Energy Saving Ordinance (EnEV) 2014, Germany, 2014. https://enev-online.com/enev_2014_volltext

[23] D.B. Crawley, Building simulation for policy support, in: Build. Perform. Simul. Des. Oper., Routledge, Second edition. | Abingdon, Oxon ; New York, NY : Routledge, 2019., 2019: pp. 384–395. https://doi.org/10.1201/9780429402296-12

[24] C.J. Hopfe, J.L.M. Hensen, Uncertainty analysis in building performance simulation for design support, Energy Build. 43 (2011) 2798–2805. https://doi.org/10.1016/j.enbuild.2011.06.034

[25] Passivhaus Institut, Passive House requirements, (2015) (accessed July 8, 2020) https://passiv.de/en/02_informations/02_passive-house-requirements/02_passive-house-requirements.htm

[26] AEA Harwell, Green Public Procurement – Windows Technical Background Report, Brussels., 2010. https://ec.europa.eu/environment/gpp/pdf/windows_GPP_background_report.pdf

[27] All Weather Windows, Glass Performance Chart, (2021) accessed December 25, 2021). https://www.allweatherwindows.com/the-pros/architect/glass-performance-chart

[28] L. Van Gelder, H. Janssen, S. Roels, Probabilistic design and analysis of building performances: Methodology and application example, Energy Build. 79 (2014) 202–211. https://doi.org/10.1016/j.enbuild.2014.04.042

[29] International Organization for Standardization, Thermal performance of buildings - Determination of air permeability of buildings - Fan Pressurization method, 2015. https://www.iso.org/standard/55718.html

[30] P. de Wilde, W. Tian, Predicting the performance of an office under climate change: A study of metrics, sensitivity and zonal resolution, Energy Build. 42 (2010) 1674–1684. https://doi.org/10.1016/j.enbuild.2010.04.011

[31] M. Picco, R. Lollini, M. Marengo, Towards energy performance evaluation in early stage building design: A simplification methodology for commercial building models, Energy Build. 76 (2014) 497–505. https://doi.org/10.1016/j.enbuild.2014.03.016

[32] K. Menberg, Y. Heo, R. Choudhary, Sensitivity analysis methods for building energy models: Comparing computational costs and extractable information, Energy Build. 133 (2016) 433–445. https://doi.org/10.1016/j.enbuild.2016.10.005

[33] US Department of Energy, EnergyPlus 8.9.0, (2018). https://energyplus.net/documentation

[34] Energy Systems Research Unit, A Tour of ESP-r, (2018) (accessed July 4, 2020). http://www.esru.strath.ac.uk/Courseware/ESP-r/tour/uncertainty.html

[35] Solar Energy Laboratory University of Wisconsin-Madison, TRNSYS: A Transient Simulation Program, (2020). https://sel.me.wisc.edu/trnsys/features/features.html

[36] Michael Wetter, Kyle Benne, Baptiste Ravache, Software Architecture and Implementation of Modelica Buildings Library Coupling for Spawn of EnergyPlus, in: 2021: pp. 325–334. https://doi.org/10.3384/ecp21181325

[37] M. Wetter, M. Fuchs, P. Grozman, L. Helsen, F. Jorissen, D. Müller, C. Nytsch-Geusen, D. Picard, P. Sahlin, M. Thorade, IEA EBC Annex 60 Modelica Library - An international collaboration to develop a free open-source model library for buildings and community energy systems, Proc. Build. Simul. 2015. (2015) 395–402. https://www.researchgate.net/publication/301676262

[38] K. Amasyali, N. Gohary, N.M. El-Gohary, A review of data-driven building energy consumption prediction studies, Renew. Sustain. Energy Rev. 81 (2018) 1192–1205. https://doi.org/10.1016/j.rser.2017.04.095

[39] P. Westermann, R. Evins, Surrogate modelling for sustainable building design – A review, Energy Build. 198 (2019) 170–186. https://doi.org/10.1016/j.enbuild.2019.05.057

[40] P. Westermann, M. Welzel, R. Evins, Using a deep temporal convolutional network as a building energy surrogate model that spans multiple climate zones, Appl. Energy. 278 (2020) 115563. https://doi.org/10.1016/j.apenergy.2020.115563

[41] H. Zhao, F. Magoulès, A review on the prediction of building energy consumption, Renew. Sustain. Energy Rev. 16 (2012) 3586–3592. https://doi.org/10.1016/j.rser.2012.02.049

[42] S. Singaravel, J. Suykens, P. Geyer, Deep convolutional learning for general early design stage prediction models, Adv. Eng. Informatics. 42 (2019) 100982. https://doi.org/10.1016/j.aei.2019.100982

[43] L. Van Gelder, P. Das, H. Janssen, S. Roels, Comparative study of metamodelling techniques in building energy simulation: Guidelines for practitioners, Simul. Model. Pract. Theory. 49 (2014) 245–257. https://doi.org/10.1016/j.simpat.2014.10.004

[44] S. Singaravel, Machine Learning for Energy Performance Prediction in Early Design Stage of Buildings, KU Leuven, 2020. https://www.researchgate.net/publication/339473161

[45] J.-S. Chou, D.-K. Bui, Modeling heating and cooling loads by artificial intelligence for energy-efficient building design, Energy Build. 82 (2014) 437–446. https://doi.org/10.1016/j.enbuild.2014.07.036

[46] T. Catalina, J. Virgone, E. Blanco, Development and validation of regression models to predict monthly heating demand for residential buildings, Energy Build. 40 (2008) 1825–1832. https://doi.org/10.1016/j.enbuild.2008.04.001

[47] P. Geyer, S. Singaravel, Component-based machine learning for performance prediction in building design, Appl. Energy. 228 (2018) 1439–1453. https://doi.org/10.1016/j.apenergy.2018.07.011.

[48] S. Singaravel, J. Suykens, P. Geyer, Deep-learning neural-network architectures and methods: Using component-based models in building-design energy prediction, Adv. Eng. Informatics. 38 (2018) 81–90. https://doi.org/10.1016/j.aei.2018.06.004

[49] Y. Li, Z. O'Neill, L. Zhang, J. Chen, P. Im, J. DeGraw, Grey-box modeling and application for building energy simulations - A critical review, Renew. Sustain. Energy Rev. 146 (2021) 111174. https://doi.org/10.1016/j.rser.2021.111174

[50] T. Berthou, P. Stabat, R. Salvazet, D. Marchio, Development and validation of a gray box model to predict thermal behavior of occupied office buildings, Energy Build. 74 (2014) 91–100. https://doi.org/10.1016/j.enbuild.2014.01.038

[51] A. Andriamamonjy, Automated workflows for building design and operation using openBIM and Modelica, (2018). https://lirias.kuleuven.be/handle/123456789/629634

[52] P. Geyer, A. Schlüter, Automated metamodel generation for Design Space Exploration and decision-making – A novel method supporting performance-oriented building design and retrofitting, Appl. Energy. 119 (2014) 537–556. https://doi.org/10.1016/j.apenergy.2013.12.064

[53] C. Eastman, P. Teicholz, R. Sacks, K. Liston, BIM Handbook: A Guide to Building Information Modeling for Owners, Managers, Designers, Engineers and Contractors, John Wiley & Sons, Inc., Hoboken, NJ, USA, NJ, USA, 2008. https://doi.org/10.1002/9780470261309

[54] K. Negendahl, Building performance simulation in the early design stage: An introduction to integrated dynamic models, Autom. Constr. 54 (2015) 39–53. https://doi.org/10.1016/j.autcon.2015.03.002

[55] P. Fazio, H.S. He, A. Hammad, M. Horvat, IFC-Based Framework for Evaluating Total Performance of Building Envelopes, J. Archit. Eng. 13 (2007) 44–53. https://doi.org/10.1061/(ASCE)1076-0431(2007)13:1(44)

[56] K.U. Ahn, Y.J. Kim, C.S. Park, I. Kim, K. Lee, BIM interface for full vs. semi-automated building energy simulation, Energy Build. 68 (2014) 671–678. https://doi.org/10.1016/j.enbuild.2013.08.063

[57] A. Andriamamonjy, D. Saelens, R. Klein, An automated IFC-based workflow for building energy

performance simulation with Modelica, Autom. Constr. 91 (2018) 166–181. https://doi.org/10.1016/j.autcon.2018.03.019

[58] H. Harter, M.M. Singh, P. Schneider-Marin, W. Lang, P. Geyer, Uncertainty Analysis of Life Cycle Energy Assessment in Early Stages of Design, Energy Build. 208 (2020) 109635. https://doi.org/10.1016/j.enbuild.2019.109635

[59] H.E. Beck, N.E. Zimmermann, T.R. McVicar, N. Vergopolan, A. Berg, E.F. Wood, Present and future Köppen-Geiger climate classification maps at 1-km resolution, Sci. Data. 5 (2018) 180214. https://doi.org/10.1038/sdata.2018.214

[60] I. De Jaeger, G. Reynders, D. Saelens, Quantifying Uncertainty Propagation For The District Energy Demand Using Realistic Variations On Input Data, in: Build. Simul. Conf. Proc., 2019: pp. 3636–3644. https://doi.org/10.26868/25222708.2019.210923

[61] I. M. Sobol, Global sensitivity indices for nonlinear mathematical models and their Monte Carlo estimates, Math. Comput. Simul. 55 (2001) 271–280. https://doi.org/10.1016/S0378-4754(00)00270-6

[62] A. Halevy, P. Norvig, F. Pereira, The Unreasonable Effectiveness of Data, IEEE Intell. Syst. 24 (2009) 8–12. https://doi.org/10.1109/MIS.2009.36

[63] C. Sun, A. Shrivastava, S. Singh, A. Gupta, Revisiting Unreasonable Effectiveness of Data in Deep Learning Era, in: 2017 IEEE Int. Conf. Comput. Vis., IEEE, 2017: pp. 843–852. https://doi.org/10.1109/ICCV.2017.97

[64] M.-Y. Cheng, M.-T. Cao, Accurately predicting building energy performance using evolutionary multivariate adaptive regression splines, Appl. Soft Comput. 22 (2014) 178–188. https://doi.org/10.1016/j.asoc.2014.05.015.

[65] A. Saltelli, S. Tarantola, F. Campolongo, M. Ratto, Methods Based on Decomposing the Variance of the Output, in: Sensit. Anal. Pract., John Wiley & Sons, Ltd, Chichester, UK, 2004: pp. 109–149. https://doi.org/10.1002/0470870958.ch5

[66] P. Geyer, M.M. Singh, S. Singaravel, Component-Based Machine Learning for Energy Performance Prediction by MultiLOD Models in the Early Phases of Building Design, in: Adv. Comput. Strateg. Eng., 2018: pp. 516–534. https://doi.org/10.1007/978-3-319-91635-4_27

[67] M. Yalcinkaya, V. Singh, Patterns and trends in Building Information Modeling (BIM) research: A Latent Semantic Analysis, Autom. Constr. 59 (2015) 68–80. https://doi.org/10.1016/j.autcon.2015.07.012

[68] Intergovernmental Panel on Climate Change, Summary for policymakers, in: O. Edenhofer, R. Pichs-Madruga, Y. Sokona, J.C. Minx, E. Farahani, S. Kadner, K. Seyboth, A. Adler, I. Braum, S. Brunner, P. Eickemeier, B. Kriemann, J. Savolainen, S. Schlömer, C. von Stechow, T. Zwickel (Eds.), Clim. Chang. 2014 Mitig. Clim. Chang., Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 2014: pp. 1–31. https://www.ipcc.ch/site/assets/uploads/2018/02/ipcc_wg3_ar5_full.pdf

[69] W. Tian, Y. Heo, P. de Wilde, Z. Li, D. Yan, C.S. Park, X. Feng, G. Augenbroe, A review of uncertainty analysis in building energy assessment, Renew. Sustain. Energy Rev. 93 (2018) 285–

301. https://doi.org/10.1016/j.rser.2018.05.029

[70] F. Campolongo, A. Saltelli, Sensitivity analysis of an environmental model: an application of different analysis methods, Reliab. Eng. Syst. Saf. 57 (1997) 49–69. https://doi.org/10.1016/S0951-8320(97)00021-5

[71] V. Corrado, H.E. Mechri, Uncertainty and Sensitivity Analysis for Building Energy Rating, J. Build. Phys. 33 (2009) 125–156. https://doi.org/10.1177/1744259109104884

[72] I. Macdonald, P. Strachan, Practical application of uncertainty analysis, Energy Build. 33 (2001) 219–227. https://doi.org/10.1016/S0378-7788(00)00085-2

[73] C. Hopfe, J. Hensen, W. Plokker, Uncertainty and Sensitivity Analysis for Detailed Design Support, Build. Simul. 2007. (2007) 1799–1804 http://www.ibpsa.org/proceedings/BS2007/p486_final.pdf

[74] G.A. Faggianelli, L. Mora, R. Merheb, Uncertainty quantification for Energy Savings Performance Contracting: Application to an office building, Energy Build. 152 (2017) 61–72 https://doi.org/10.1016/j.enbuild.2017.07.022

[75] C. Struck, Jan Hensen, P. Kotek, On the Application of Uncertainty and Sensitivity Analysis with Abstract Building Performance Simulation Tools, J. Build. Phys. 33 (2009) 5–27. https://doi.org/10.1177/1744259109103345

[76] W. Tian, P. de Wilde, Uncertainty and sensitivity analysis of building performance using probabilistic climate projections: A UK case study, Autom. Constr. 20 (2011) 1096–1109. https://doi.org/10.1016/j.autcon.2011.04.011

[77] S. Yang, W. Tian, E. Cubi, Q. Meng, Y. Liu, L. Wei, Comparison of Sensitivity Analysis Methods in Building Energy Assessment, Procedia Eng. 146 (2016) 174–181. https://doi.org/10.1016/j.proeng.2016.06.369

[78] W. Tian, A review of sensitivity analysis methods in building energy analysis, Renew. Sustain. Energy Rev. 20 (2013) 411–419. https://doi.org/10.1016/j.rser.2012.12.014

[79] J.S. Hygh, J.F. DeCarolis, D.B. Hill, S. Ranji Ranjithan, Multivariate regression as an energy assessment tool in early building design, Build. Environ. 57 (2012) 165–175. https://doi.org/10.1016/j.buildenv.2012.04.021

[80] J.C. Helton, J.D. Johnson, C.J. Sallaberry, C.B. Storlie, Survey of sampling-based methods for uncertainty and sensitivity analysis, Reliab. Eng. Syst. Saf. 91 (2006) 1175–1209. https://doi.org/10.1016/j.ress.2005.11.017

[81] A. Saltelli, P. Annoni, I. Azzini, F. Campolongo, M. Ratto, S. Tarantola, Variance based sensitivity analysis of model output. Design and estimator for the total sensitivity index, Comput. Phys. Commun. 181 (2010) 259–270. https://doi.org/10.1016/j.cpc.2009.09.018

[82] A.-T. Nguyen, S. Reiter, A performance comparison of sensitivity analysis methods for building energy models, Build. Simul. 8 (2015) 651–664. https://doi.org/10.1007/s12273-015-0245-4

[83] T.A. Mara, S. Tarantola, Application of global sensitivity analysis of model output to building thermal simulations, Build. Simul. 1 (2008) 290–302.

https://doi.org/10.1007/s12273-008-8129-5

[84] G. Calleja Rodríguez, A. Carrillo Andrés, F. Domínguez Muñoz, J.M. Cejudo López, Y. Zhang, Uncertainties and sensitivity analysis in building energy simulation using macroparameters, Energy Build. 67 (2013) 79–87. https://doi.org/10.1016/j.enbuild.2013.08.009

[85] T.L. Hemsath, K. Alagheband Bandhosseini, Sensitivity analysis evaluating basic building geometry's effect on energy use, Renew. Energy. 76 (2015) 526–538. https://doi.org/10.1016/j.renene.2014.11.044

[86] Sefaira, Zoning Strategy - One Zone per Floor, (2017) (accessed December 25, 2021). https://support.sefaira.com/hc/en-us/articles/115000093271

[87] S. Asadi, S.S. Amiri, M. Mottahedi, On the development of multi-linear regression analysis to assess energy consumption in the early stages of building design, Energy Build. 85 (2014) 246–255. https://doi.org/10.1016/j.enbuild.2014.07.096

[88] E. Neufert, P. Neufert, Neufert Architects' Data, Fifth, Blackwell Publishing Ltd, West Sussex, UK, 2019. https://www.wiley.com/en-us/-p-9781119284352

[89] M. Vollmer, P. Schneider-Marin, H. Harter, W. Lang, Ferd. Tausendpfund | Innovation, Faculty of Architecture, TU Munich, Munich, Germany, 2020. https://www.tausendpfund.group/dateien/Innovation_2020.pdf

[90] A. Saltelli, S. Tarantola, On the Relative Importance of Input Factors in Mathematical Models, J. Am. Stat. Assoc. 97 (2002) 702–709. https://doi.org/10.1198/016214502388618447

[91] A. Saltelli, M. Ratto, T. Andres, F. Campolongo, J. Cariboni, D. Gatelli, M. Saisana, S. Tarantola, Global Sensitivity Analysis. The Primer, John Wiley & Sons, Ltd, Chichester, UK, 2008. https://doi.org/10.1002/9780470725184

[92] F. Campolongo, J. Cariboni, A. Saltelli, An effective screening design for sensitivity analysis of large models, Environ. Model. Softw. 22 (2007) 1509–1518 https://doi.org/10.1016/j.envsoft.2006.10.004

[93] J. Herman, W. Usher, SALib: An open-source Python library for Sensitivity Analysis, J. Open Source Softw. 2 (2017) 97. https://doi.org/10.21105/joss.00097

[94] M.M. Singh, S. Singaravel, P. Geyer, Improving Prediction Accuracy of Machine Learning Energy Prediction Models, in: B. Kumar, F.P. Rahimian, D. Greenwood, T. Hartmann (Eds.), Proc. 36th CIB W78 2019 Conf., Newcastle, UK, 2019: pp. 102–112. https://www.researchgate.net/publication/337772121

[95] E. Molenbroek, M. Smith, N. Surmeli, S. Schimschar, P. Waide, J. Tait, C. McAllister, Savings and benefits of global regulations for energy efficient products, Eur. Union. (2015). https://ec.europa.eu/energy/sites/ener/files/documents/Cost of Non-World - Final Report.pdf

[96] M. Hamdy, A.-T. Nguyen, J.L.M. Hensen, A performance comparison of multi-objective optimization algorithms for solving nearly-zero-energy-building design problems, Energy Build. 121 (2016) 57–71. https://doi.org/10.1016/j.enbuild.2016.03.035

[97] T. Østergård, R.L. Jensen, S.E. Maagaard, Building simulations supporting decision making in

early design – A review, Renew. Sustain. Energy Rev. 61 (2016) 187–201. https://doi.org/10.1016/j.rser.2016.03.045

[98] C.J. Hopfe, G.L.M. Augenbroe, J.L.M. Hensen, Multi-criteria decision making under uncertainty in building performance assessment, Build. Environ. 69 (2013) 81–90. https://doi.org/10.1016/j.buildenv.2013.07.019

[99] M.M. Singh, P. Geyer, Statistical decision assistance for determining energy-efficient options in building design under uncertainty, in: P. Geyer, K. Allacker, M. Schevenels, F. De Troyer, Pieter Pauwels (Eds.), 26th Int. Work. Intell. Comput. Eng., Leuven, 2019. http://ceur-ws.org/Vol-2394/paper08.pdf

[100] I. Jaffal, C. Inard, A metamodel for building energy performance, Energy Build. 151 (2017) 501–510. https://doi.org/10.1016/j.enbuild.2017.06.072

[101] T. Østergård, R.L. Jensen, S.E. Maagaard, A comparison of six metamodeling techniques applied to building performance simulations, Appl. Energy. 211 (2018) 89–103. https://doi.org/10.1016/j.apenergy.2017.10.102

[102] N.D. Roman, F. Bre, V.D. Fachinotti, R. Lamberts, Application and characterization of metamodels based on artificial neural networks for building performance simulation: A systematic review, Energy Build. 217 (2020) 109972. https://doi.org/10.1016/j.enbuild.2020.109972

[103] M.M. Singh, S. Singaravel, R. Klein, P. Geyer, Quick energy prediction and comparison of options at the early design stage, Adv. Eng. Informatics. 46 (2020) 101185. https://doi.org/10.1016/j.aei.2020.101185

[104] R.E. Edwards, J. New, L.E. Parker, B. Cui, J. Dong, Constructing large scale surrogate models from big data and artificial intelligence, Appl. Energy. 202 (2017) 685–699. https://doi.org/10.1016/j.apenergy.2017.05.155

[105] M. Banko, E. Brill, Scaling to very very large corpora for natural language disambiguation, in: Proc. 39th Annu. Meet. Assoc. Comput. Linguist. - ACL '01, Association for Computational Linguistics, Morristown, NJ, USA, 2001: pp. 26–33. https://doi.org/10.3115/1073012.1073017

[106] J. Cho, K. Lee, E. Shin, G. Choy, S. Do, How much data is needed to train a medical image deep learning system to achieve necessary high accuracy?, (2015). http://arxiv.org/abs/1511.06348

[107] J. Hestness, S. Narang, N. Ardalani, G. Diamos, H. Jun, H. Kianinejad, M.M.A. Patwary, Y. Yang, Y. Zhou, Deep Learning Scaling is Predictable, Empirically, (2017). https://doi.org/1712.00409v1

[108] L. Van Gelder, H. Janssen, S. Roels, Metamodelling in robust low-energy dwelling design, 2nd Cent. Eur. Symp. Build. Physics, Sept. 9-11. (2013) 93–99. https://lirias.kuleuven.be/retrieve/237485

[109] G. Pruthi, F. Liu, S. Kale, M. Sundararajan, Estimating Training Data Influence by Tracing Gradient Descent, in: H. Larochelle, M. Ranzato, R. Hadsell, M.F. Balcan, H. Lin (Eds.), Adv. Neural Inf. Process. Syst., Curran Associates, Inc., Vancouver, Canada, 2020: pp. 19920–19930. https://proceedings.neurips.cc/paper/2020/file/e6385d39ec9394f2f3a354d9d2b88eec-Paper.pdf

[110] R. Jin, W. Chen, A. Sudjianto, An efficient algorithm for constructing optimal design of computer experiments, J. Stat. Plan. Inference. 134 (2005) 268–287. https://doi.org/10.1016/j.jspi.2004.02.014

[111] S. Joe, F.Y. Kuo, Remark on Algorithm 659: Implementing Sobol's Quasirandom Sequence Generator, ACM Trans. Math. Softw. 29 (2003) 49–57. https://doi.org/10.1145/641876.641879

[112] T.W. Simpson, J.D. Poplinski, P.N. Koch, J.K. Allen, Metamodels for Computer-based Engineering Design: Survey and recommendations, Eng. Comput. 17 (2001) 129–150. https://doi.org/10.1007/PL00007198

[113] R.T. Johnson, D.C. Montgomery, B. Jones, P.A. Parker, Comparing Computer Experiments for Fitting High-Order Polynomial Metamodels, J. Qual. Technol. 42 (2010) 86–102. https://doi.org/10.1080/00224065.2010.11917808

[114] G. Palacios, R. Carlos, Optimal Data Distributions in Machine Learning, California Institute of Technology, 2015. https://doi.org/10.7907/Z9DR2SD5

[115] A. Jain, M. Upreti, P. Jyothi, Improved Accented Speech Recognition Using Accent Embeddings and Multi-task Learning, in: Interspeech 2018, ISCA, ISCA, 2018: pp. 2454–2458. https://doi.org/10.21437/Interspeech.2018-1864

[116] J.J. Humphries, P.C. Woodland, D. Pearce, Using accent-specific pronunciation modelling for robust speech recognition, in: Proceeding Fourth Int. Conf. Spok. Lang. Process. ICSLP '96, IEEE, n.d.: pp. 2324–2327. https://doi.org/10.1109/ICSLP.1996.607273

[117] T. Hayashi, K. Gyohten, H. Ohki, T. Takami, A Study of Data Augmentation for Handwritten Character Recognition using Deep Learning, in: 2018 16th Int. Conf. Front. Handwrit. Recognit., IEEE, 2018: pp. 552–557. https://doi.org/10.1109/ICFHR-2018.2018.00102

[118] C. Shorten, T.M. Khoshgoftaar, A survey on Image Data Augmentation for Deep Learning, J. Big Data. 6 (2019) 60. https://doi.org/10.1186/s40537-019-0197-0

[119] K. Konis, A. Gamas, K. Kensek, Passive performance and building form: An optimization framework for early-stage design support, Sol. Energy. 125 (2016) 161–179. https://doi.org/10.1016/j.solener.2015.12.020

[120] T. Han, Q. Huang, A. Zhang, Q. Zhang, Simulation-based decision support tools in the early design stages of a green building-A review, Sustain. 10 (2018). https://doi.org/10.3390/su10103696

[121] A. Hollberg, T. Lichtenheld, N. Klüber, J. Ruth, Parametric real-time energy analysis in early design stages: a method for residential buildings in Germany, Energy, Ecol. Environ. 3 (2018) 13–23. https://doi.org/10.1007/s40974-017-0056-9

[122] Z. Li, J. Dai, H. Chen, B. Lin, An ANN-based fast building energy consumption prediction method for complex architectural form at the early design stage, Build. Simul. 12 (2019) 665–681. https://doi.org/10.1007/s12273-019-0538-0

[123] M.M. Singh, P. Geyer, Examining and improving accuracy in a deep learning-based pipeline for the prediction of building energy demand, in: L.C. Ungureanu, T. Hartmann (Eds.), EG-ICE 2020

Work. Intell. Comput. Eng., Universitätsverlag der TU Berlin, Berlin, 2020: pp. 62–72. http://dx.doi.org/10.14279/depositonce-9977

[124] B.K. Flury, H. Riedwyl, Standard Distance in Univariate and Multivariate Analysis, Am. Stat. 40 (1986) 249. https://doi.org/10.2307/2684560

[125] D. Edelmann, D. Richards, D. Vogel, The Distance Standard Deviation, (2017). http://arxiv.org/abs/1705.05777

[126] M.M. Singh, P. Geyer, Information requirements for multi-level-of-development BIM using sensitivity analysis for energy performance, Adv. Eng. Informatics. 43 (2020) 101026. https://doi.org/10.1016/j.aei.2019.101026

[127] A. Géron, Hands-On Machine Learning with Scikit-Learn and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems, Ninth, O'Reilly Media, Inc., Sebastopol, CA, CA, 2017. https://www.oreilly.com/library/view/hands-on-machine-learning/9781491962282/

[128] I.T. Jolliffe, J. Cadima, Principal component analysis: a review and recent developments, Philos. Trans. R. Soc. A Math. Phys. Eng. Sci. 374 (2016) 20150202. https://doi.org/10.1098/rsta.2015.0202

[129] S.C. Ng, Principal component analysis to reduce dimension on digital image, Procedia Comput. Sci. 111 (2017) 113–119. https://doi.org/10.1016/j.procs.2017.06.017

[130] F. Chollet, Keras, (2015) (accessed May 6, 2019). https://keras.io

[131] A.Y. Ng, Feature selection, L 1 vs. L 2 regularization, and rotational invariance, in: Twenty-First Int. Conf. Mach. Learn. - ICML '04, ACM Press, New York, New York, USA, 2004: p. 78. https://doi.org/10.1145/1015330.1015435

[132] T. Zhang, B. Yu, Boosting with early stopping: Convergence and consistency, Ann. Stat. 33 (2005) 1538–1579. https://doi.org/10.1214/009053605000000255

[133] M.M. Singh, Data increment and enrichment to train component-based machine learning model for early stage energy prediction, (2021). https://doi.org/10.17632/gcrf95w6kg.2

[134] B. Lee, N. Pourmousavian, J.L.M. Hensen, Full-factorial design space exploration approach for multi-criteria decision making of the design of industrial halls, Energy Build. 117 (2016) 352–361. https://doi.org/10.1016/j.enbuild.2015.09.028

[135] J.A. Clarke, J.L.M. Hensen, Integrated building performance simulation: Progress, prospects and requirements, Build. Environ. 91 (2015) 294–306. https://doi.org/10.1016/j.buildenv.2015.04.002

[136] M. Browne, S.S. Ghidary, Convolutional Neural Networks for Image Processing: An Application in Robot Vision, in: 2003: pp. 641–652. https://doi.org/10.1007/978-3-540-24581-0_55

[137] D. Ciresan, U. Meier, J. Masci, L.M. Gambardella, J. Schmidhuber, Flexible, High Performance Convolutional Neural Networks for Image Classification., 2011. https://doi.org/10.5591/978-1-57735-516-8/IJCAI11-21

[138] A. Krizhevsky, I. Sutskever, G.E. Hinton, ImageNet classification with deep convolutional neural networks, Commun. ACM. 60 (2017) 84–90. https://doi.org/10.1145/3065386

[139] M. Płoszaj-Mazurek, E. Ryńska, M. Grochulska-Salak, Methods to Optimize Carbon Footprint of Buildings in Regenerative Architectural Design with the Use of Machine Learning, Convolutional Neural Network, and Parametric Design, Energies. 13 (2020) 5289. https://doi.org/10.3390/en13205289

[140] The Mathworks, Introducing Deep Learning with MATLAB: "What is Deep Learning?," MathWorks, Inc. MATLAB Simulink Are Regist. Trademarks MathWorks, Inc. (2018) 1–14. https://de.mathworks.com/content/dam/mathworks/ebook/gated/80879v00_Deep_Learning_ebook.pdf

[141] M.M. Singh, Developing ML Models for Early Stage Building Energy Prediction (using CNN), (2022). https://doi.org/10.17632/9kk26h4w6s.2

[142] Autodesk Inc., Revit | BIM Software, (2021) (accessed July 19, 2020). https://www.autodesk.com/products/revit

[143] P. de Wilde, G. Augenbroe, M. van der Voorden, Design analysis integration: supporting the selection of energy saving building components, Build. Environ. 37 (2002) 807–816. https://doi.org/10.1016/S0360-1323(02)00053-7

[144] T. Østergård, R.L. Jensen, S.E. Maagaard, Early Building Design: Informed decision-making by exploring multidimensional design space using sensitivity analysis, Energy Build. 142 (2017) 8–22. https://doi.org/10.1016/j.enbuild.2017.02.059

[145] A. Mahdavi, A comprehensive computational environment for performance based reasoning in building design and evaluation, Autom. Constr. 8 (1999) 427–435. https://doi.org/10.1016/S0926-5805(98)00089-2

[146] C. Bleil de Souza, S. Tucker, Thermal simulation software outputs: a framework to produce meaningful information for design decision-making, J. Build. Perform. Simul. 8 (2015) 57–78. https://doi.org/10.1080/19401493.2013.872191

[147] F. Ritter, P. Geyer, A. Bormann, Simulation-based Decision-making in Early Design Stages, in: Proceeding 32nd CIB W78 Conf., 2015: pp. 657–666. https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.725.1760

[148] A. Schlueter, F. Thesseling, Building information model based energy/exergy performance assessment in early design stages, Autom. Constr. 18 (2009) 153–163. https://doi.org/10.1016/j.autcon.2008.07.003

[149] T. Méndez Echenagucia, A. Capozzoli, Y. Cascone, M. Sassone, The early design stage of a building envelope: Multi-objective search through heating, cooling and lighting energy performance analysis, Appl. Energy. 154 (2015) 577–591. https://doi.org/10.1016/j.apenergy.2015.04.090

[150] C. Underwood, F.W.H. Yik, Modelling Methods for Energy in Buildings, Blackwell Publishing Ltd, Oxford, UK, 2004. https://doi.org/10.1002/9780470758533

[151] K. Tupper, C. Fluhrer, Energy modeling at each design phase: strategies to minimize design energy use, Proc. SimBuild; 2010 SimBuild 2010. (2010). http://ibpsa-usa.org/index.php/ibpusa/article/view/271/260

[152] M. Wetter, Modelica-based modelling and simulation to support research and development in building energy and control systems, J. Build. Perform. Simul. 2 (2009) 143–161 https://doi.org/10.1080/19401490902818259

[153] P. de Wilde, The gap between predicted and measured energy performance of buildings: A framework for investigation, Autom. Constr. 41 (2014) 40–49. https://doi.org/10.1016/j.autcon.2014.02.009

[154] E. Cuerda, O. Guerra-Santin, J.J. Sendra, F.J. Neila, Understanding the performance gap in energy retrofitting: Measured input data for adjusting building simulation models, Energy Build. 209 (2020) 109688. https://doi.org/10.1016/j.enbuild.2019.109688

[155] R. Jones, A. Fuertes, P. Wilde, The gap between simulated and measured energy performance: A case study across six identical new-build flats in the UK, Build. Simul. (2015) http://www.ibpsa.org/proceedings/BS2015/p2171.pdf

[156] C. van Dronkelaar, M. Dowson, C. Spataru, D. Mumovic, A Review of the Regulatory Energy Performance Gap and Its Underlying Causes in Non-domestic Buildings, Front. Mech. Eng. 1 (2016). https://doi.org/10.3389/fmech.2015.00017

[157] J. Khoury, Z. Alameddine, P. Hollmuller, Understanding and bridging the energy performance gap in building retrofit, Energy Procedia. 122 (2017) 217–222. https://doi.org/10.1016/j.egypro.2017.07.348

[158] P.A. Strachan, G. Kokogiannakis, I.A. Macdonald, History and development of validation with the ESP-r simulation program, Build. Environ. 43 (2008) 601–609. https://doi.org/10.1016/j.buildenv.2006.06.025

[159] D.H. Nall, D.B. Crawley, Energy simulation in the building design process: mainframe computer simulation programs for energy analysis can provide important information throughout the building design process.(Reprint), ASHRAE J. 53 (2011) 36. https://www.researchgate.net/publication/255150741

[160] N. Jones, C.J. McCrone, B.J. Walter, K.B. Pratt, D.P. Greenberg, Automated translation and thermal zoning of digital building models for energy analysis, in: Proc. BS 2013 13th Conf. Int. Build. Perform. Simul. Assoc., 2013: pp. 202–209. http://www.ibpsa.org/proceedings/BS2013/p_1027.pdf

[161] B. Urban, L. Glicksman, The MIT Design Advisor – A Fast, Simple Tool for Energy Efficient Building Design, in: Proc. SimBuild, 2006. https://www.ibpsa.us/sites/default/files/publications/SB06_270_276.pdf

[162] S. de Wit, G. Augenbroe, Uncertainty Analysis of Building Design Evaluations, Build. Simul. (2001) 319–326. https://www.researchgate.net/publication/251961428

[163] R. Rezaee, J. Brown, G. Augenbroe, J. Kim, Assessment of uncertainty and confidence in building design exploration, Artif. Intell. Eng. Des. Anal. Manuf. 29 (2015) 429–441. https://doi.org/10.1017/S0890060415000426

[164] M. Hollander, J. Sethuraman, Nonparametric Statistics: Rank-Based Methods, in: Int. Encycl. Soc. Behav. Sci., Elsevier, 2015: pp. 891–897.

https://doi.org/10.1016/B978-0-08-097086-8.42157-4

[165] The AIA Energy Modeling Working Group, An Architect's Guide to Integrating Energy Modeling in the Design Process, 2012. http://content.aia.org/sites/default/files/2016-04/Energy-Modeling-Design-Process-Guide.pdf

[166] B. Griffith, N. Long, P. Torcellini, R. Judkoff, D. Crawley, J. Ryan, Methodology for Modeling Building Energy Performance across the Commercial Sector, Golden, Colorado, 2008. https://www.nrel.gov/docs/fy08osti/41956.pdf

[167] P. Shiel, S. Tarantino, M. Fischer, Parametric analysis of design stage building energy performance simulation models, Energy Build. 172 (2018) 78–93. https://doi.org/10.1016/j.enbuild.2018.04.045

[168] Y. Chen, T. Hong, Impacts of building geometry modeling methods on the simulation results of urban building energy models, Appl. Energy. 215 (2018) 717–735. https://doi.org/10.1016/j.apenergy.2018.02.073

[169] T. Dogan, C. Reinhart, P. Michalatos, Autozoner: an algorithm for automatic thermal zoning of buildings with unknown interior space definitions, J. Build. Perform. Simul. 9 (2016) 176–189. https://doi.org/10.1080/19401493.2015.1006527

[170] T. Dogan, E. Saratsis, C. Reinhart, The optimization potential of floor-plan typologies in early design energy modeling, in: Proc. BS2015 14th Conf. Int. Build. Perform. Simul. Assoc., Hyderabad, India, 2015. http://www.ibpsa.org/proceedings/BS2015/p2455.pdf

[171] L. Smith, Beyond the Shoebox: Thermal Zoning Approaches for Complex Building Shapes, ASHRAE Trans. 118 (2012) 141–148. https://de0qmbqba3hfm.cloudfront.net/attachments/75565/0

[172] JAMES J. HIRSCH & ASSOCIATES, eQUEST Introductory Tutorial, Camarillo, CA, 2009. http://doe2.com/download/equest/eQ-v3-63_Introductory-Tutorial.pdf

[173] Sefaira, Zoning Strategy - Perimeter / Core, (2017) (accessed December 16, 2019). https://support.sefaira.com/hc/en-us/articles/115000093632-Zoning-Strategy-Perimeter-Core

[174] M. Shin, J.S. Haberl, Thermal zoning for building HVAC design and energy simulation: A literature review, Energy Build. 203 (2019) 109429. https://doi.org/10.1016/j.enbuild.2019.109429

[175] cove.tool, Single Zone vs Multi Zone Energy Model for Early Stage Design, (2019). https://www.cove.tools/single-zone-vs-multi-zone-energy-model-for-early-stage-design

[176] A. Schlueter, P. Geyer, Linking BIM and Design of Experiments to balance architectural and technical design factors for energy performance, Autom. Constr. 86 (2018) 33–43. https://doi.org/10.1016/j.autcon.2017.10.021

[177] B. Wauman, H. Breesch, D. Saelens, Evaluation of the accuracy of the implementation of dynamic effects in the quasi steady-state calculation method for school buildings, Energy Build. 65 (2013) 173–184. https://doi.org/10.1016/j.enbuild.2013.05.046

[178] I. Ballarini, E. Primo, V. Corrado, On the limits of the quasi-steady-state method to predict the

energy performance of low-energy buildings, Therm. Sci. 22 (2018) 1117–1127. https://doi.org/10.2298/TSCI170724133B

[179] A. Moronis, C. Koulamas, A. Kalogeras, Validation of a monthly quasi-steady-state simulation model for the energy use in buildings, in: 2017 22nd IEEE Int. Conf. Emerg. Technol. Fact. Autom., IEEE, 2017: pp. 1–6. https://doi.org/10.1109/ETFA.2017.8247665

[180] B. Wauman, Evaluation of the quasi-steady-state method for the assessment of energy use in school buildings, (2015). https://lirias.kuleuven.be/handle/123456789/507727

[181] G. Pernigotto, A. Gasparella, Quasi-steady state and dynamic simulation approaches for the calculation of building energy needs: Part 1 thermal losses, in: Build. Simul. Appl., 2013: pp. 293–302. http://www.ibpsa.org/proceedings/BSA2013/31.pdf

[182] A. Andriamamonjy, R. Klein, D. Saelens, Automated grey box model implementation using BIM and Modelica, Energy Build. 188–189 (2019) 209–225. https://doi.org/10.1016/j.enbuild.2019.01.046

[183] H. Gao, C. Koch, Y. Wu, Building information modelling based building energy modelling: A review, Appl. Energy. 238 (2019) 320–343. https://doi.org/10.1016/j.apenergy.2019.01.032

[184] J.B. Kim, W. Jeong, M.J. Clayton, J.S. Haberl, W. Yan, Developing a physical BIM library for building thermal energy simulation, Autom. Constr. 50 (2015) 16–28. https://doi.org/10.1016/j.autcon.2014.10.011

[185] A. Karola, H. Lahtela, R. Hänninen, R. Hitchcock, Q. Chen, S. Dajka, K. Hagström, BSPro COM-Server—interoperability between software tools using industrial foundation classes, Energy Build. 34 (2002) 901–907. https://doi.org/10.1016/S0378-7788(02)00066-X

[186] V. Bazjanac, Building energy performance simulation as part of interoperable software environments, Build. Environ. 39 (2004) 879–883. https://doi.org/10.1016/j.buildenv.2004.01.012

[187] K. Negendahl, T.R. Nielsen, Building energy optimization in the early design stages: A simplified method, Energy Build. 105 (2015) 88–99. https://doi.org/10.1016/j.enbuild.2015.06.087

[188] C. Struck, Uncertainty propagation and sensitivity analysis techniques in building performance simulation to support conceptual building and system design, Technische Universiteit Eindhoven, 2012. http://purl.tue.nl/220546028097.pdf

[189] ASHRAE, Standard 90.1-2013. Energy Standard for Buildings Except Low-Rise Residential Buildings, Atlanta, GA, 2013. www.ashrae.org

[190] G.W. Corder, D.I. Foreman, Nonparametric statistics for non-statisticians: a step-by-step approach, Second, Wiley, 2014. https://www.wiley.com/en-us/-p-9781118165881

[191] S.A. Julious, Sample sizes for clinical trials with Normal data, Stat. Med. 23 (2004) 1921–1986. https://doi.org/10.1002/sim.1783

[192] ASHRAE Standards Committee, Energy standard for buildings except low-rise residential buildings, Atlanta, GA : American Society of Heating, Refrigerating and Air-Conditioning Engineers, ASHRAE, [2010] ©2010, Atlanta, GA, 2016.

https://doi.org/https://www.ashrae.org/technical-resources/bookstore/standard-90-1

[193] S. de Wit, G. Augenbroe, Analysis of uncertainty in building design evaluations and its implications, Energy Build. 34 (2002) 951–958. https://doi.org/10.1016/S0378-7788(02)00070-1

[194] Deutsches Institut für Normung e. V., Energy efficiency of buildings - Calculation of the net, final and primary energy demand for heating, cooling, ventilation, domestic hot water and lighting, Germany, 2018. https://www.din.de/en/getting-involved/standards-committees/nabau/publications/wdc-beuth:din21:293515783

[195] H. Johra, P.K. Heiselberg, J. Le Dréau, Numerical Analysis of the Impact of Thermal Inertia from the Furniture / Indoor Content and Phase Change Materials on the Building Energy Flexibility, Build. Simul. 2017. (2017) 35–42. https://doi.org/10.26868/25222708.2017.012

[196] T. Hong, Z. Wang, X. Luo, W. Zhang, State-of-the-art on research and applications of machine learning in the building life cycle, Energy Build. 212 (2020) 109831. https://doi.org/10.1016/j.enbuild.2020.109831

[197] A. Sawhney, M.M. Singh, R. Ahuja, Worldwide BIM Overview, in: P. Wu, H. Li, X. Wang (Eds.), Integr. Build. Inf. Model., Bentham Science, 2017: pp. 1–45. https://doi.org/10.2174/9781681084572117010 1

[198] M.M. Singh, P. Geyer, CNN-based Quick Energy Prediction Model using Image Analysis for Shape Information, in: 17th Int. IBPSA Build. Simul. Conf., Brugges, Belgium, 2021. https://www.researchgate.net/publication/354420055

[199] M.M. Singh, S. Singaravel, P. Geyer, Machine learning for early stage building energy prediction: Increment and enrichment, Appl. Energy. 304 (2021) 117787. https://doi.org/10.1016/j.apenergy.2021.117787

[200] M.M. Singh, P. Schneider-Marin, H. Harter, W. Lang, P. Geyer, Applying Deep Learning and Databases for Energy- efficient Architectural Design, in: L.C. Werner, D. Koering (Eds.), Proc. 38th ECCADe Conf. Eucation Res. Comput. Aided Archit. Des. Eur., eCAADe (Education and Research in Computer Aided Architectural Design in Europe), Berlin, Germany, 2020: pp. 79–87. http://ecaade.org/downloads/eCAADe2020_volume2-print.pdf

[201] S. Alsaadani, C. Bleil De Souza, Architect–BPS consultant collaborations: Harmony or hardship?, J. Build. Perform. Simul. 11 (2018) 391–413. https://doi.org/10.1080/19401493.2017.1379092

[202] B. Welle, J. Haymaker, Z. Rogers, ThermalOpt: A methodology for automated BIM-based multidisciplinary thermal simulation for use in optimization environments, Build. Simul. 4 (2011) 293–313. https://doi.org/10.1007/s12273-011-0052-5

[203] D.J. Gerber, S.-H.E. Lin, Designing in complexity: Simulation, integration, and multidisciplinary design optimization for architecture, Simulation. 90 (2014) 936–959. https://doi.org/10.1177/0037549713482027

[204] J. Park, J. Park, J. Kim, J. Kim, Building information modelling based energy performance

assessment system, Constr. Innov. 12 (2012) 335–354. https://doi.org/10.1108/14714171211244587

[205] R. Rezaee, J. Brown, J. Haymaker, G. Augenbroe, A new approach to performance-based building design exploration using linear inverse modeling, J. Build. Perform. Simul. 12 (2019) 246–271. https://doi.org/10.1080/19401493.2018.1507046

[206] C. Hopfe, C. Struck, P. Kotek, J. van Schijndel, J. Hensen, W. Plokker, Uncertainty Analysis for Building Performance Simulation – a Comparison of Four Tools, in: Proc. Build. Simul. 2007, 2007: pp. 1383–1388. http://www.ibpsa.org/proceedings/BS2007/p504_final.pdf

[207] M. Wetter, J. Wright, A comparison of deterministic and probabilistic optimization algorithms for nonsmooth simulation-based optimization, Build. Environ. 39 (2004) 989–999. https://doi.org/10.1016/j.buildenv.2004.01.022

[208] R. Evins, A review of computational optimisation methods applied to sustainable building design, Renew. Sustain. Energy Rev. 22 (2013) 230–245. https://doi.org/10.1016/j.rser.2013.02.004

[209] A.-T. Nguyen, S. Reiter, P. Rigo, A review on simulation-based optimization methods applied to building performance analysis, Appl. Energy. 113 (2014) 1043–1058. https://doi.org/10.1016/j.apenergy.2013.08.061

[210] R.H. Sprague, A Framework for the Development of Decision Support Systems, MIS Q. 4 (1980) 1–26. https://doi.org/10.2307/248957

[211] A. Kaklauskas, G. Dzemyda, L. Tupenaite, I. Voitau, O. Kurasova, J. Naimaviciene, Y. Rassokha, L. Kanapeckiene, Artificial Neural Network-Based Decision Support System for Development of an Energy-Efficient Built Environment, Energies. 11 (2018) 1994. https://doi.org/10.3390/en11081994

[212] S. Attia, J.L.M. Hensen, L. Beltrán, A. De Herde, Selection criteria for building performance simulation tools: contrasting architects' and engineers' needs, J. Build. Perform. Simul. 5 (2012) 155–169. https://doi.org/10.1080/19401493.2010.549573

[213] Deutsches Institut für Normung e. V., Thermal performance of buildings - Transmission and ventilation heat transfer coefficients, Germany, 2018. https://doi.org/10.31030/2560190

[214] M.M. Singh, Validation of Early Design Stage EnergyPlus Model for Office Building (one-zone-per-floor model), (2020). https://doi.org/10.17632/5kskbt6w2s.1

[215] M.M. Singh, Validation of Early Design Stage EnergyPlus Model for Office Building, (2020). https:/dx.doi.org/10.17632/x6xwvb2r9r.1

[216] J.E. Jackson, A user's guide to principal components, Wiley, New York (N.Y.), 1991. https://www.wiley.com/en-us/-p-9780471471349

[217] E. Jones, T. Oliphant, P. Peterson, Others, SciPy: Open source scientific tools for Python, (2019). (accessed June 12, 2019) http://www.scipy.org

[218] M.E. Wall, A. Rechtsteiner, L.M. Rocha, Singular Value Decomposition and Principal Component Analysis, in: A Pract. Approach to Microarray Data Anal., Kluwer Academic

Publishers, Boston, 2003: pp. 91–109. https://doi.org/10.1007/0-306-47815-3_5

[219] R.E. Madsen, L.K. Hansen, O. Winther, Singular Value Decomposition and Principal Component Analysis, (2004) 13–16. http://www2.imm.dtu.dk/pubdb/edoc/imm4000.pdf

[220] H. Hoffmann, Kernel PCA for novelty detection, Pattern Recognit. 40 (2007) 863–874. https://doi.org/10.1016/j.patcog.2006.07.009

[221] G.E. Hinton, Reducing the Dimensionality of Data with Neural Networks, Science (80-.). 313 (2006) 504–507. https://doi.org/10.1126/science.1127647

[222] L. van der Maaten, G. Hinton, Visualizing Data using t-SNE, J. Mach. Learn. Res. 9 (2008) 2579–2605. http://jmlr.org/papers/v9/vandermaaten08a.html

[223] M. Sonka, V. Hlavac, R. Boyle, The image, its mathematical and physical background, in: Image Process. Anal. Mach. Vision-Cengage Learn., 2014: p. 930. https://vdoc.pub/documents/image-processing-analysis-and-machine-vision-sr3vpsib4vk0

[224] W. Hernandez, A. Mendez, Application of Principal Component Analysis to Image Compression, in: Stat. - Grow. Data Sets Grow. Demand Stat., InTech, 2018. https://doi.org/10.5772/intechopen.75007

[225] P. Tao, X. Feng, C. Wen, Image Recognition Based on Two-Dimensional Principal Component Analysis Combining with Wavelet Theory and Frame Theory, J. Control Sci. Eng. 2018 (2018) 1–7. https://doi.org/10.1155/2018/9061796

[226] A.C. Depoian, L.E. Jaques, D. Xie, C.P. Bailey, P. Guturu, Neural network image fusion with PCA preprocessing, in: F. Ahmad, P.P. Markopoulos, B. Ouyang (Eds.), Big Data III Learn. Anal. Appl., SPIE, 2021: p. 19. https://doi.org/10.1117/12.2588039

[227] M.M. Singh, Verification of Early Design Stage Machine Learning Model using EnergyPlus Simulation Data, (2020). https://doi.org/10.17632/ms56cbx7dy.1

[228] M.M. Singh, Developing ML Models for Early Stage Building Energy Prediction (using CNN), (2022). https://doi.org/10.17632/9kk26h4w6s.3



manav.mahan.singh@live.in

manav@p-energyanalysis.de

www.p-energyanalysis.de

manav-mahan-singh-871928b1

January 24, 1989

English (proficient user)

Hindi (native speaker)

German (beginner)

Manav Mahan Singh

Experience

Software Developer *Nov 2021-Present*
CADSys GmBH, Chemnitz, Germany
Plugin for Autodesk Products to automate modelling

Doctoral Fellow *May 2017 – Oct 2021*
KU Leuven, Belgium
Energy Analysis, BIM API, and Machine Learning

Assistant Architect *Feb 2016 – Apr 2017*
Central Public Works Department, India
Design, Planning and Construction of Public Buildings

Assistant Professor *Jul 2015 - Feb 2016*
RICS School of Built Environment, India
BIM Research, Construction Management Teaching

Research Associate *Aug 2014 - Jun 2015*
RICS School of Built Environment, India
Research and Development of BIM API

Education

PhD (Engineering Sciences) *Apr 2018-Mar 2022*
KU Leuven, Belgium
BIM and Machine Learning Development

M. Tech. (Civil Engineering) *(2012-14)*
Indian Institute of Technology, Delhi
Thesis at Chair of Computational Modelling & Simulation at TU Munich

B. Arch. *(2007-12)*
Gautam Buddh Technical University, Lucknow
Silver Medal

Relevant Courses

Object-Oriented Data Structures in C++ Ordered Data Structures Unordered Data Structures	*Coursera | Online | 2021*
Building Information Modelling	*TU Munich | 2014*
Modelling Languages (UML)	*VU Brussels | 2018*
Machine Learning	*Coursera Stanford | Online | 2020*
Methodology and Statistics	*Flames Summer School | 2019*
Building Simulations	*KU Leuven | 2018*

Scholarships And Awards

“Visiting Researcher” at ETH Zurich	*ASL Scholarship 2020*
“Winner” in Student Competition	*Digital Construction Brussels, 2018*
“First prize" at National Level	*3D Student Design Challenge, Autodesk, 2013*
“Visiting Scholar” at TU Munich	*DAAD Scholarship, 2013-14*
“Teaching Assistantship”	*IIT Delhi, 2012-14*
“Silver Medal” in Architecture	*GBTU Lucknow, 2012*
“Rank 2" at National Level	*GATE 2012*

Programming Languages

Python, C++, and C# (advanced)

Developed deep Learning and convolutional neural network models using TensorFlow
Machine learning model deployment on a webserver

JavaScript, PHP, CSS, HTML, Bash (intermediate)

Developed easy-to-navigate user interface and visualization using Plotly
Used PHP to create login interface and handle Ajax request to access and modify database

Software And Applications

Amazon Web Services - EC2, SES, and Lambda

Webserver using EC2 Linux-based instance and SES to setup mail service
Created docker container using Node.js for AWS lambda function to perform ML inference

Apache Webserver and MySQL

Used for running different components of webserver for the website

Autodesk Revit and EnergyPlus

Used parametric modelling, visual programming (Dynamo), API development, and generated synthetic data to train and test machine learning models using EnergyPlus

Journal Articles

Automation in Construction, 136

M.M. Singh, C. Deb, P. Geyer, Early-stage design support combining machine learning and building information modelling, Autom. Constr. 136 (2022) 104147. https://doi.org/10.1016/j.autcon.2022.104147.

Applied Energy, 304

M.M. Singh, S. Singaravel, P. Geyer, Machine learning for early stage building energy prediction: Increment and enrichment, Appl. Energy. 304 (2021) 117787. https://doi.org/10.1016/j.apenergy.2021.117787.

Advanced Engineering Informatics, 46

Singh, M. M., Singaravel, S., Klein, R., & Geyer, P. (2020). Quick energy prediction and comparison of options at the early design stage. https://doi.org/10.1016/j.aei.2020.101185

Advanced Engineering Informatics, 43

Singh, M. M., & Geyer, P. (2020). Information requirements for multi-level-of-development BIM using sensitivity analysis for energy performance. https://doi.org/10.1016/j.aei.2019.101026

International Journal of Construction Management, 19 (1)

Singh, M. M., Sawhney, A., & Borrmann, A. (2019). Integrating rules of modular coordination to improve model authoring in BIM. https://doi.org/10.1080/15623599.2017.1358077

Construction Economics and Building, 17 (4)

Singh, M. M., Sawhney, A., & Sharma, V. (2017). Utilising Building Component Data from BIM for Formwork Planning. https://doi.org/10.5130/AJCEB.v17i4.5546

Procedia Engineering, 123

Singh, M. M., Sawhney, A., & Borrmann, A. (2015). Modular Coordination and BIM: Development of Rule Based Smart Building Components. https://doi.org/10.1016/j.proeng.2015.10.104

Energy and Buildings, 208

Harter, H., **Singh, M. M.,** Schneider-Marin, P., Lang, W., & Geyer, P. (2020). Uncertainty Analysis of Life Cycle Energy Assessment in Early Stages of Design. https://doi.org/10.1016/j.enbuild.2019.109635

Journal of Information Technology in Construction, 25

Abualdenien, J., Schneider-Marin, P., Zahedi, A., Harter, H., Exner, H., Steiner, D., **Mahan Singh, M.,** Borrmann, A., Lang, W., Petzold, F., König, M., Geyer, P., & Schnellenbach-Held, M. (2020). Consistent management and evaluation of building models in the early design stages. 212–232. https://doi.org/10.36680/j.itcon.2020.013

Book Chapter

Integrated Building Information Modelling

Sawhney, A., **Singh, M. M.,** & Ahuja, R. (2017). Worldwide BIM Overview. In P. Wu, H. Li, & X. Wang (Eds.), Bentham Science. https://doi.org/10.2174/9781681084572117010l

Conference Articles (with presentation)

Building Simulation 2021, Bruges, Belgium

Singh, M. M., & Geyer, P. (2021). CNN-based Quick Energy Prediction Model using Image Analysis for Shape Information. https://www.researchgate.net/publication/354420055

eCAADe 2020, Berlin, Germany

Singh, M. M., Schneider-Marin, P., Harter, H., Lang, W., & Geyer, P. (2020). Applying Deep Learning and Databases for Energy- efficient Architectural Design. http://ecaade.org/downloads/eCAADe2020_volume2-print.pdf

EG-ICE 2020, Berlin, Germany

Singh, M. M., & Geyer, P. (2020). Examining and improving accuracy in a deep learning-based pipeline for the prediction of building energy demand. http://dx.doi.org/10.14279/depositonce-9977

CIB W78 2019, New Castle, UK

Singh, M. M., Singaravel, S., & Geyer, P. (2019). Improving Prediction Accuracy of Machine Learning Energy Prediction Models. https://www.researchgate.net/publication/337772121

EG-ICE 2019, Leuven, Belgium

Singh, M. M., & Geyer, P. (2019). Statistical decision assistance for determining energy-efficient options in building design under uncertainty. http://ceur-ws.org/Vol-2394/paper08.pdf

IALCCE 2018, Ghent, Belgium

Singh, M. M., Singaravel, S., & Geyer, P. (2018). Information Exchange Scenarios between Machine Learning Energy Prediction Model and BIM at Early Stage of Design. https://www.researchgate.net/publication/337771841

EG-ICE 2018, Lausanne, Switzerland

Geyer, P., **Singh, M. M.,** & Singaravel, S. (2018). Component-Based Machine Learning for Energy Performance Prediction by MultiLOD Models in the Early Phases of Building Design. https://doi.org/10.1007/978-3-319-91635-4_27

Creative Construction Conference, 2015, Krakow, Poland

Singh, M. M., Sawhney, A., & Borrmann, A. (2015). Rule based Building Components for Modular Coordination

Conference Articles

X. Chen, **M.M. Singh**, P. Geyer, Component-based machine learning for predicting representative time- series of energy performance in building design, 28th Eur. Gr. Intell. Comput. Eng. (EG-ICE 2021), Berlin, Germany, 2021. https://depositonce.tu-berlin.de/handle/11303/13226

Singh, M. M., Sawhney, A., Sharma, V., & Kumari, S. P. (2016). Exploring Potentials of Using BIM Data for Formwork Design through API Development. *Proceedings of ID@50 Integrated Design Conference, 29 June – 1 July 2016*. University of Bath.

Sawhney, A., **Singh, M. M.,** & Sharma, V. (2016). Building Information Modelling and International Property Measurement Standards: Promising Prospects. *Proceedings of ID@50 Integrated Design Conference, 29 June – 1 July 2016*. University of Bath.

FACULTY OF ENGINEERING SCIENCE
DEPARTMENT OF ARCHITECTURE
ARCHITECTURAL ENGINEERING DIVISION
Kasteelpark Arenberg 1, box 2431
B-3001 HEVERLEE, BELGIUM
tel. + 32 16 32 1361
manavmahan.singh@kuleuven.be
www.architectuur.kuleuven.be