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

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ABSTRACT

The concept of multi-Level-of-Development (multi-LOD) modelling represents a flexible approach of information management and compilation in building information modelling (BIM) on a set of consistent levels. From an energy perspective during early architectural design, the refinement of design parameters by addition of information allows a more precise prediction of building performance. The need for energy-efficient buildings requires a designer to focus on the parameters in order of their ability to reduce uncertainty in energy performance to prioritise energy relevant decisions. However, there is no method for assigning and prioritising information for a particular level of multi-LOD. In this study, we performed a sensitivity analysis of energy models to estimate the uncertainty caused by the design parameters in energy prediction. This study allows to rank the design parameters in order of their influence on the energy prediction and determine the information required at each level of multi-LOD approach. We have studied the parametric energy model of different building shapes representing architectural design variation at the early design stage. A variance-based sensitivity analysis method is used to calculate the uncertainty contribution of each design parameter. The three levels in the uncertainty contribution by the group of parameters are identified which form the basis of information required at each level of multi-LOD BIM approach. The first level includes geometrical parameters, the second level includes technical specification and operational design parameters, and the third level includes window construction and system efficiency parameters. These findings will be specifically useful in the development of a multi-LOD approach to prioritise performance relevant decisions at early design phases.

## 1. Introduction

The process of building design is described as an increase in information in the digital model. However, the process of building design involves switching between levels, described as scaling [1,2]. The concept of multi-Level-of-Development (multi-LOD) addresses this situation by integrating performance prediction and enabling informed decision-making [3,4]. Multi-LOD is based on the concept of defining design parameters with uncertainty in the beginning and, at each level of development, few parameters are focussed and a suitable value is assigned to these parameters as explained in Fig. 1. This approach is more appropriate to represent the evolutionary and iterative nature of the design process [5]. However, it lacks a method based on engineering information for defining the levels and information required at each level. For the inherent prioritisation, we introduce the use of sensitivity analysis to ascertain which of the design parameters should be focussed at each level of multi-LOD. In addition, this research quantitively estimates the uncertainty caused by the design parameters in energy prediction using sensitivity analysis method. A variance-based sensitivity measure represents the uncertainty in model outcome caused by a parameter or the uncertainty which can be removed from predictions by defining the value of the parameter [6,7].

Since the building energy models are deterministic in nature, it will deliver only one estimation of energy performance without considering any uncertainty in parameters. But, due to the inherent uncertainty in design parameters and related information at an early stage of design, it is required to make a probabilistic estimate of the energy performance [8]. The probabilistic estimation of energy performance is made by sampling the design parameters in their uncertainty ranges. This probabilistic estimation of energy performance needs to be addressed by a statistical approach [9]. As the design process progresses, the design parameters are defined more precisely, thus, resulting in a more accurate estimation of the performance.

The energy-efficient solutions have been one of the prime focus of

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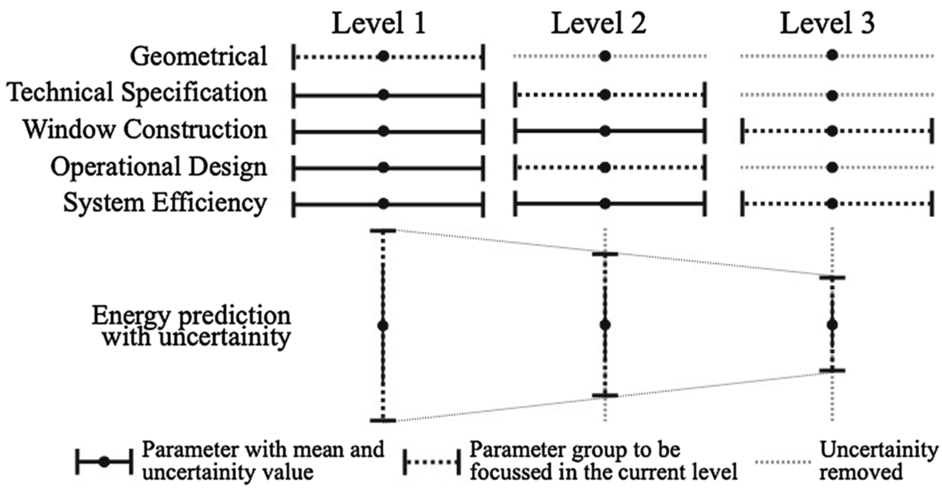


**Fig. 1.** Parametric uncertainty in a multi-LOD approach.

research in building design, given that approximately one-third of global energy is required to operate the buildings [10,11]. Thus, it will be imperative for a designer to focus on the design parameters with strong influence at the beginning to reliably reduce the uncertainty in the energy prediction and develop energy-efficient building designs further. Sensitivity analysis of energy models is performed to prioritise the design parameters in order of their influence on energy consumption. Previous research works examine the energy models of buildings with fixed architectural shape and size [7,12–14] or rectangular building of variable size [15,16]. However, fixing the shape is not representative of the early stage of design when an architect is interested in developing the building shape. The behaviour of parameters is expected to be influenced by the building shape and should be studied before extending the results to the early stage of design. There are research works focussed on finding an optimal building shapes based on energy performance [17–19] and multi-criteria optimisation [20]. However, these approaches overlook the designer's involvement in the design process [21,22]. The underlying concept of this research is to assist the designers by identifying the most important design parameters (information), thus suggesting them to focus on some selected parameters at each level of multi-LOD. The three research gaps addressed in this research paper can be summarized as follows. Firstly, earlier research works do not study the effect of design parameters in the energy model of different building shapes. Secondly, previous researches estimate uncertainity caused by individual parameters while the uncertainty contribution by a group of parameters will provide useful information for the development of multi-LOD approach. Finally, there is a lack of study to identify the information required at each level of multi-LOD approach, focussing on energy-efficient building design.

There is a potential to streamline the design process with energy prediction by the appropriate use of building information modelling (BIM) data structures according to the multi-LOD approach [3]. This approach will be supported by focussing suitable design parameters at each level of multi-LOD approach, giving priority to the influential parameters. The focus is on the design phase of the building life cycle when the information regarding shape, size, and technical specification is being developed. The research is aimed to identify which of the design parameters should be focussed at each level of multi-LOD approach by performing a sensitivity analysis of building energy models. Thus, the objectives of the research are:

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

The paper is structured in sections – overview of sensitivity analysis methods, research methodology, results, discussion, and conclusions. The overview section documents the significance of sensitivity analysis for energy models and the selection of a sensitivity analysis method for the current research work. The research methodology section explains the representative test case, the alternative building shapes, and the calculation process of sensitivity indices and uncertainty. The results section includes the finding of the research work, *i.e.* sensitivity indices and ranking of parameters, uncertainty contribution and information requirement for multi-LOD approach. The discussion section mentions the limitations of the methodology and results. The conclusion section documents the variation in parameter ranking in building energy model at an early stage of the design and the possibility of identifying the information required in multi-LOD approach.

## 2. Overview of the sensitivity analysis method

The sensitivity analysis is becoming a more common method to study the effect of design parameters as most of the design parameter required to make energy prediction are inherently uncertain [23]. The global sensitivity analysis methods are used to rank the parameters in the order of influence and quantify the uncertainty in the output variable [24–27]. The sensitivity analysis studies in the domain are focussed on design support [28], assessing the robustness of energy models [29] and variation in the output variable [30,31]. There are various global sensitivity analysis methods, such as the Morris method, regression-based and variance-based methods, are implemented to study the effect and behaviour of design parameters in energy models [7,16,32]. Each method offers certain advantages over others based on the scenario under consideration. Morris and regression-based method assume a model structure to calculate the sensitivity indices, thus more suitable for linear models with fewer parameter interactions [33,34]. The variance-based method is more suitable for complex models because of its model-independent nature.

A building energy model is expected to contain higher-order effects and parameter interactions. Thus, the variance-based method is more suitable for the building energy model under consideration [35]. There are two sensitivity indices calculated using the variance-based method, *i.e.* first order effect $S$, and total effect $S^T$. First order effect is an estimate of the fraction of variance, *i.e.* uncertainty in the model output, which can be removed if a value is assigned to it [7]. Thus, it is suitable to identify the parameters with significant influence on the model output [36,37]. The higher value of $S$ shows the higher effect of the design parameter on the model output and better the rank. The value of $S^T$ represents the effect of design parameters, 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 [38].

## 3. Research methodology

The research methodology section consists of three sub-sections. Sub-section 3.1 describes the test case with alternative building shapes. Sub-section 3.2 provides the details of parameters studied and their selection. Sub-section 3.3 describes the implementation of sensitivity analysis method, calculation procedure for sensitivity indices and uncertainty contribution, and details out the number of adequate samples for variance-based sensitivity analysis.

### 3.1. Test case

The sensitivity analysis study starts from a rectangular floor plan building – the Tausendpfund test case. The selected building is a representative of an average-sized office building with the total floor area of 1200 (14.8 × 27.0 × 3) m$^2$, equally distributed on three floors and floor-to-floor height of 3.26 m. This building is located in Regensburg near Munich, Germany. The climate of Munich is classified as Cfb (warm temperate – fully humid – warm summer) in Köppen-Geiger climate classification, which represents most of western Europe [39]. The building follows the 5-day schedule with the heating and cooling set point as of 20 and 24 °C and setback point of 10 and 28 °C respectively. The occupant load is one person per 10 m$^2$. The energy includes the energy required to maintain thermal comfort, provide lighting and operate the equipment. The effect of available daylight to reduce the requirement of artificial lighting is also considered. The external envelope of the building plays a significant role in determining building energy consumption compare to internal space divisions [40]. Thus, for the simplicity of the simulation model, the *one-zone-per-floor* calculation method is used, which assumes there is only one thermal zone is present at each floor [4,41].

The early stage of design is represented by the test case and alternative building shapes (Fig. 2). All shapes are configured to provide the same floor area. Alternative shapes support the objective to have a representative range of design variants for the early design phase in order to assess sensitivities and parametric range correctly. The shapes 1, 2, 3, 4, 5, and 6 represent rectangular, plus-shape, L-shape, U-shape, H-shape and T-shape floor plans respectively. The mentioned geometrical configurations are commonly used shapes in small and medium-size office building design [17,41,42]. The selected building shapes are orthogonal to match the typical design of such office buildings. They are suitable to represent the possible variation at an early stage of design with a limited number of geometrical parameters. Six geometrical parameters, which are *Length, Width, Height, the ratio for LengthA (rLenA)*, the *ratio for WidthA (rWidA)* and *Orientation*, represent further variation in size. *rLenA* and *rWidA* are the ratio of *LengthA* to *Length* and *WidthA* to *Width,* respectively. *LengthA* and *WidthA* for each shape are mentioned in Fig. 2.

**Table 1**
Details of design parameters.

| Group | Parameter | Symbol | Unit | Min | Max |
|---|---|---|---|---|---|
| Geometrical | Length | L | meters | 13 | 16.75 |
| | Width | W | | 23.5 | 30.2 |
| | Height | H | | 8.1 | 9.9 |
| | Ratio for LengthA | rLenA | – | 0.7 | 0.9 |
| | Ratio for WidthA | rWidA | | 0.7 | 0.9 |
| | Orientation | Ori | degrees | 15 | 25 |
| Technical Specifications | Wall U-Value | U_Wall | W/m$^2$°K | 0.21 | 0.35 |
| | Ground Floor U-Value | U_GFloor | | 0.26 | 0.44 |
| | Roof U-Value | U_Roof | | 0.15 | 0.25 |
| | Infiltration | Infil | ACH | 0.45 | 0.75 |
| Window Construction | Window U-Value | U_Window | W/m$^2$°K | 0.98 | 1.63 |
| | Window g-Value | g_Window | – | 0.45 | 0.90 |
| | WWR (North) | WWR_N | | 0.23 | 0.38 |
| | WWR (West) | WWR_W | | 0.23 | 0.38 |
| | WWR (South) | WWR_S | | 0.23 | 0.38 |
| | WWR (East) | WWR_E | | 0.23 | 0.38 |
| Operational Design | Light & Electrical Heat Gain | L/EHG | W/m$^2$ | 15 | 25 |
| | Operating Hours | OpH | hours | 8 | 10 |
| System Efficiency | Boiler Efficiency | B_Eff | – | 0.8 | 0.9 |
| | Chiller COP | C_COP | | 3 | 5 |

### 3.2. Definition of parameter space

The effect of parameters on energy prediction, listed in Table 1, forms the basis for the study. The dimensions have been constrained so

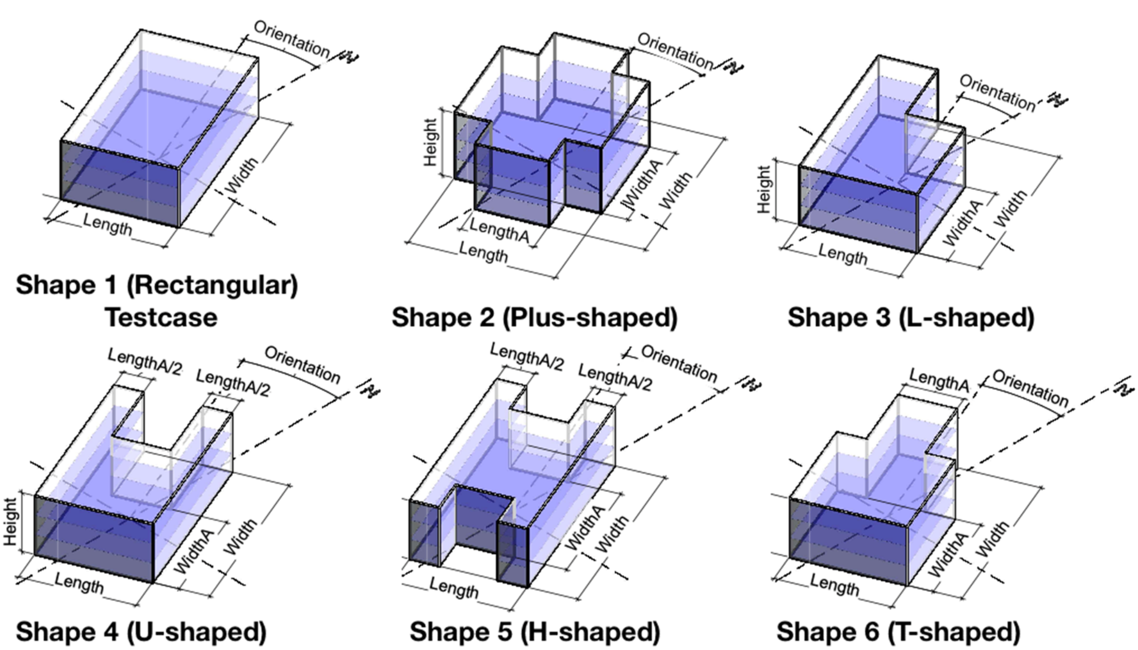


**Fig. 2.** Architectural design variations studied in the research.

that the total floor area is always in the range of 1200 ± 25% sqm, and length to width ratio is close to the testcase building. This adjustment is required to make the results comparable. Since we are performing the sensitivity analysis on a specific building case, the dimensions are chosen according to the site restrictions and are a limited variation to the real building case. The shapes and parameters represent typical design cases; more complex designs are possible and can be extended using a similar method. Generally, the compact shape such as cube is expected to perform better than other shapes, but in the given scenario, an option is unlikely to lead to a cube because of site conditions, daylight and desired internal conditions (office rooms). The most compact shape in the given parameter range is *Shape1* with the dimensions of 13 m × 23.5 m × 9.9 m.

*Wall U-Value, Ground Floor U-Value, Roof U-Value* and *Infiltration* describes the technical specifications. *Window U-Value, Window g-Value* and *Window-to-Wall Ratios (WWRs)* for each direction define window construction. Four other parameters, which are *Operating Hours, Lighting and Electrical Heat Gain, Boiler Efficiency* and *Chiller Coefficient of Performance (COP)*, represent building operation and system efficiency. The average of the *U-values* of building components is the same as the reference building described in German regulation [43]. The minimum and maximum values are ± 25% of the average. The thermal capacitance of the constructions is kept constant with generic values for a typical construction type. The infiltration is set to 0.6 air changes per hour (ACH) with a variation of ± 25%. The *WWRs* is 0.3 and varied ± 25%. The operating hours are varied between 8 and 10 h a day during weekdays. The lighting and electrical heat gain are 20 ± 25% W/m$^2$. The boiler efficiency ranges between 0.8 and 0.9 and the chiller COP between 3 and 5. The parameters are grouped based on their nature; for instance, *L, W, rLenA, rWidA, H* and *Ori* are grouped as geometrical parameters. In total, the five parameter groups are identified as geometrical, technical specification, window construction, operational design and system efficiency parameters.

### 3.3. Calculation method

The sensitivity indices, S and $S^T$, are calculated using variance-based method as described in Saltelli et al. 2010 [35]. The calculation of sensitivity indices starts by setting up a sample matrix, followed by calculation of energy demand (model output) and analysis of model output to calculate the values of sensitivity indices. The sample matrix **X**, of size $n \times p$ representing $n$ design configurations of $p$ parameters, is set up using SALib python library [44] as shown in Eq. (1). A program developed for this research automates the generation of EnergyPlus input files corresponding to each design configuration. A building's energy demand corresponding to each design configuration is calculated using the dynamic energy simulation tool EnergyPlus [45] at the Vlaams Supercomputer Center (VSC). We used ten nodes equivalent to 360 cores at the clock speed of 2.3 GHz. The use of supercomputer allows running EnergyPlus simulations in parallel (360 simulations at a time), reducing the time required to generate data. The data generation for sensitivity analysis is fully automated. The results of EnergyPlus simulations are read using a program which provides the model output corresponding to each design configuration and represented by vector **Y**(**X**). The model output, *i.e.* vector **Y**(**X**), is analysed to calculate the sensitivity indices, $S$ and $S^T$ for each design parameter.

$$\mathbf{X} = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & \cdots & x_{1,p} \\ x_{2,1} & x_{2,2} & \cdots & \cdots & x_{2,p} \\ \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots \\ x_{n,1} & x_{n,2} & \cdots & \cdots & x_{n,p} \end{bmatrix} \quad \text{and} \quad \mathbf{Y}(\mathbf{X}) = \begin{bmatrix} y_1 \\ y_2 \\ \dots \\ \dots \\ y_n \end{bmatrix} \tag{1}$$

The parameters are ranked based on the value of their first-order effect, higher the value better the rank. 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 of the parameters. If the higher-order effects and interactions are not significant, this will provide a reliable measure of uncertainty caused by the parameter. The sum of interactions and higher-order effects is calculated by subtracting the first-order effect from total effects. The three levels are observed in the uncertainty contributed by the group of parameters, which forms the basis of information required at the three levels of multi-LOD approach. The designer should focus on parameter groups which exceed the observed level threshold.

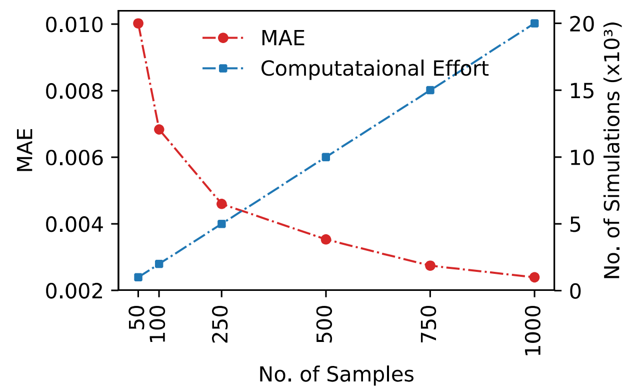


**Fig. 3.** Number of samples for variance-based methods (colour).

The required number of samples is tested by calculating the mean absolute error (MAE), described in Saltelli et al. 2010 [35]. If the number of samples is $N$, then it requires $n = N \times (p + 2)$ design configurations to generate the data for variance-based sensitivity analysis. The tests are conducted, starting with a low number of samples and gradually increasing the number of samples. The validity of the method depends on MAE, which is expected to decrease with the number of samples. The preliminary test is conducted with 50, 100, 250, 500, 750 and 1000 samples for *Shape1*. The values of MAE for the number of samples are plotted in Fig. 3. The number of simulations represents the computational efforts as the simulations are the most time-consuming activity in the process. The computational efforts increase linearly with the number of samples, but the value of MAE doesn't reduce much once the number of samples is higher than 500. So, for further analysis, the data has been collected with 500 samples for each shape.

## 4. Results

The sensitivity analysis is carried out for each shape and results are documented in this section. Section 4.1 presents the values of sensitivity indices and ranking of parameters. Section 4.2 documents the uncertainty contribution by the group of parameters and Section 4.3 details the information required at each level of multi-LOD approach.

### 4.1. First order and the total effect

The value of sensitivity indices is calculated for each parameter using 500 samples for each shape using the variance-based method. The values of $S$ and $S^T$ are plotted as a bar graph in Fig. 4. It can be noticed that there is a little variation in the parameters' sensitivities across shapes. The value of indices for parameters such as *L, W, Infil, OpH* and *L/EHG* is slightly different for *Shape1* than other shapes. The values of indices are much lower for *U-values* of components, *g_Window* and *WWRs*. The value of indices for these parameters is plotted in zoomed inset figures. The values of the first-order effect for *L, W, Infil* and *OpH* are close to 0.25, 0.25, 0.15, 0.1, making these most influential parameters. The value of $S$ and $S^T$ for WWRs is close to 0, rendering these as insignificant parameters.

The parameters are ranked based on the value of $S$ for each shape,

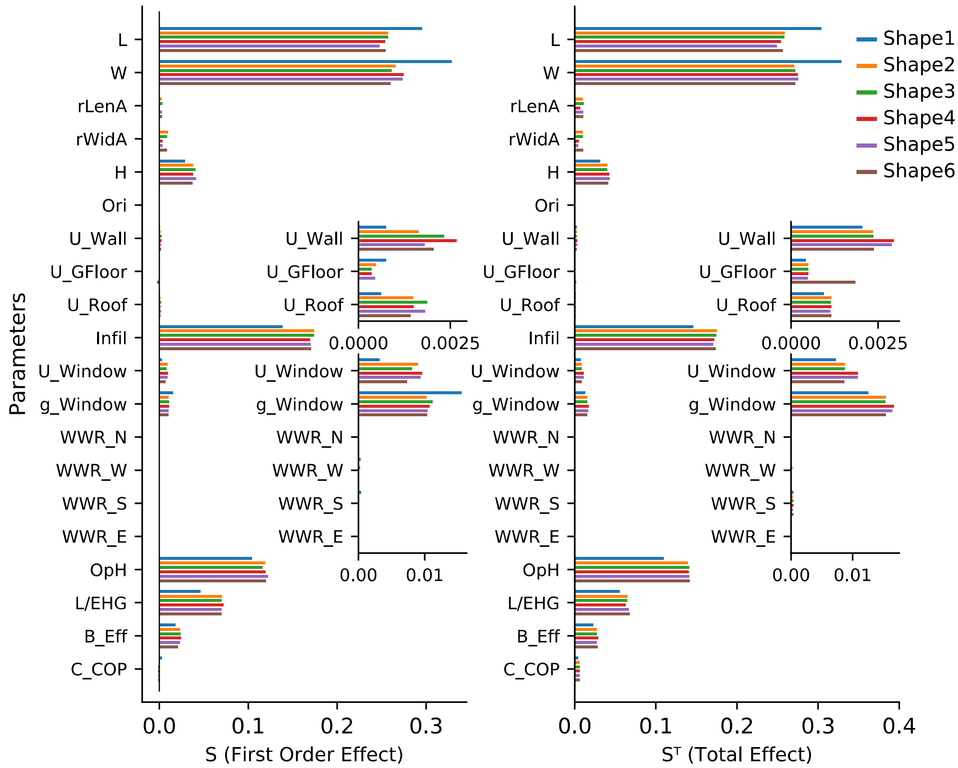


**Fig. 4.** First order and total effect for different shapes (colour).

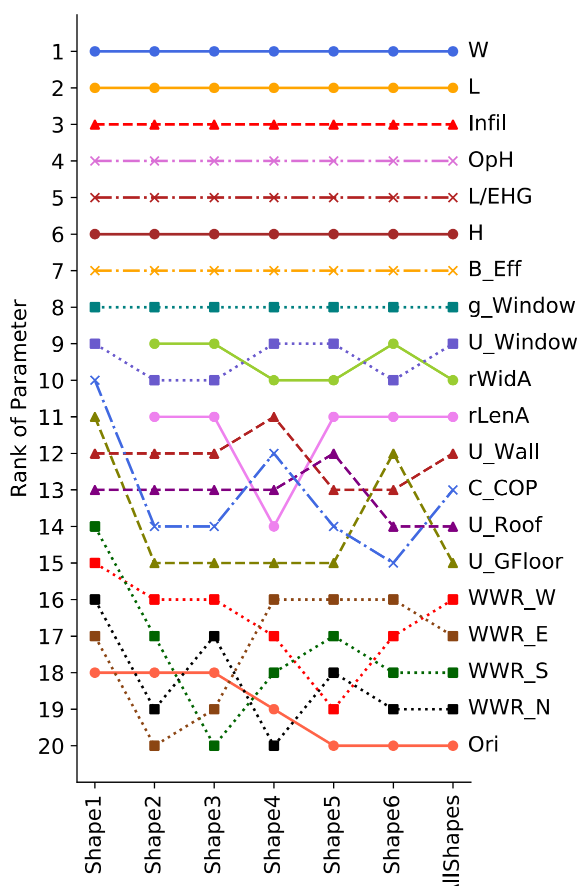


**Fig. 5.** Ranking of parameters for each design alternative (colour).

and the results are plotted as trendline in Fig. 5, higher the value, better the rank. It allows identifying any change in the ranking of parameters across different architectural designs. The ranking of parameters for *AllShapes* is based on the mean value of *S* calculated over all the shapes. There is no change in the ranking of parameters for the parameters *W, L, Infil, OpH, L/EHG, H, B_Eff* and *g_Window* and ranked in the similar order as mentioned for all the shapes. For remaining parameters, the rank of parameter changes across shapes.

### 4.2. Estimation of uncertainty in energy prediction

The uncertainty in energy prediction attributed to a group of parameters is calculated by summing up the absolute value of the first-order effect of the parameters. The sum of values of higher-order effects

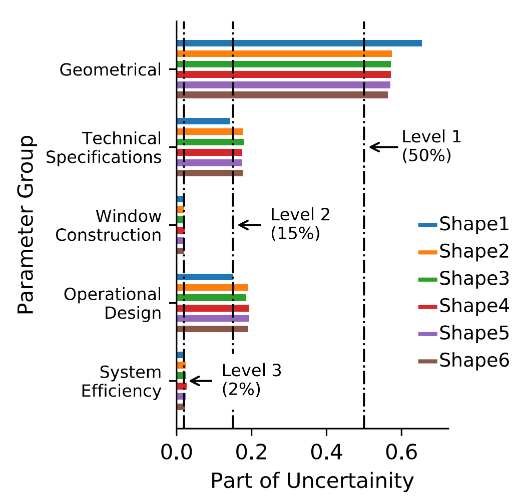


**Fig. 6.** Uncertainty contribution by a group of parameters for energy prediction (colour).

and interactions of all the parameters is close to 0.05; hence, ignored for calculating the uncertainty contribution. The results are shown in Fig. 6 for the group of parameters, namely geometrical, technical specifications, window construction, operational design, and system efficiency parameters. There seems to be no to little variation in uncertainties across different building geometry. More than 50% of the uncertainty in energy prediction is represented by geometrical parameters. The technical and operational design parameters cause 1/5 of the total uncertainty individually. Window construction and system efficiency parameters represent the uncertainty of less than 5% in the prediction.

### 4.3. Information requirement at each level of multi-LOD approach

The three levels in the uncertainty contribution by the groups of parameters are identified at 50%, 15% and 2%, as shown in Fig. 6. These levels are used to determine the information required in a multi-LOD approach. The geometrical parameters cause the most part of uncertainty for all shapes. Thus, finding the suitable value for geometrical parameters is most important and should be prioritised at the first level of multi-LOD approach. At the next level, the designer should focus on technical specifications and operational design parameter group, which causes more than 15% of uncertainty individually. At the third level, decisions on system efficiency and window construction parameters will reduce uncertainty by about 2%.

The designer assigns suitable values to the design parameters by design decisions following the order of preference at each level. The approach needs to be tested by assigning values to the design parameters and observing its effect on the uncertainty in the energy prediction at each level. The energy prediction is performed using the fixed design parameters (with an average value assigned to it) and the uncertain design parameters (random combinations) at each level. The energy prediction results are plotted in Fig. 7, with a mean value, range and interquartile range (IQR) for each shape. The range and IQR represent the uncertainty in the energy predictions. It can be noticed the uncertainty reduces as the designer assigns the value to the design parameters. The uncertainty as Level 1 is highest, followed by Level 2 and Level 3. For example, in Shape1, the mean value of energy prediction is 1.70 $\times$ $10^5$ kWh/a, ranges at Level 1, 2 and 3 are 1.32 $\times$ $10^5$ kWh/a (77%), 0.73 $\times$ $10^5$ kWh/a (43%) and 0.26 $\times$ $10^5$ kWh/a (15%) respectively. The IQRs at the same levels are 0.31 $\times$ $10^5$ kWh/a (18%), 0.18 $\times$ $10^5$ kWh/a (11%) and 0.06 $\times$ $10^5$ kWh/a (4%) respectively. It should be noted that the energy performance changes from one shape to another but (as shown in section 4.2) the parameters' sensitivities vary a little across the shapes. Thus, the shape also influences the energy performance but cannot be quantified with other design parameters due to its categorical nature.

## 5. Discussion

The parameter groups are ranked in the order of their influence on the energy prediction using the method of variance-based sensitivity analysis. It has been shown that the reduced uncertainty in the design parameters allows a more precise prediction of energy performance. Moreover, the order of the influential parameters is important as finding a suitable value for these parameters reduces the uncertainty more than the others. Thus, the order of the influential parameters forms the basis of information requirement for multi-LOD approach.

The value of indicator $S$ and the ranking of parameters based on this indicator shows *W, L, Infil, OpH, L/EHG, H* and *B_Eff* are the most influential parameters and ranked in the similar order as mentioned for all the shapes. A change in the ranking of parameters occurs with lower values of $S$ (less than 0.01) only, which means the most significant parameters show similar ranking across different architectural designs. In most of the case, *WWRs* and *Ori* shows the negligible effect and ranked in the last. It should be noted that the input range of all the parameters only varies $\pm$ 25% from the mean value. Due to non-linearity, results cannot be generalised if a higher range is defined. The ranking of parameters based on the value of $S$ for *AllShapes* is representative of early-stage design as it is calculated over several architectural designs.

The sum of values of $S$ for the first seven influential parameters is close to 0.9, which means 90% of uncertainty can be removed by finding the value of these seven design parameters. However, it is not logical to focus on these parameters at one level, as nature of these parameters is completely different. For example, a designer cannot

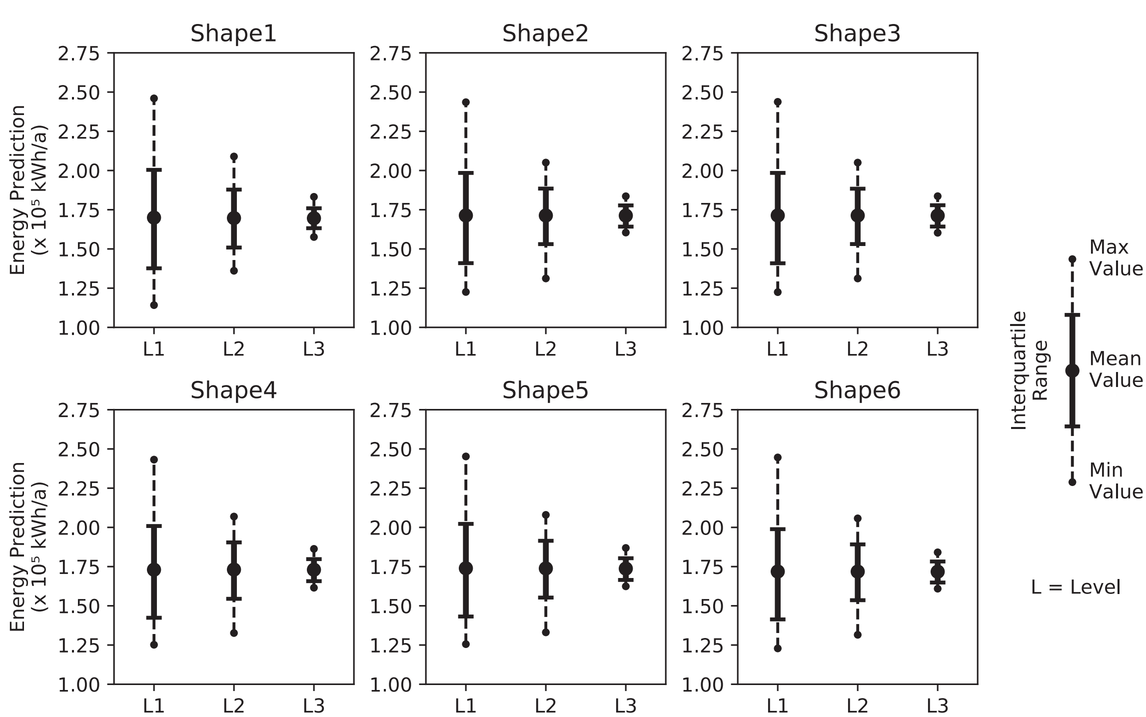


**Fig. 7.** Effect of the uncertainty in design parameters on the performance prediction.

focus on length and width with system efficiency parameters. The value of $S$ for $W$ and $L$ is close to 0.25, which means 50% of the uncertainty can be removed as soon a suitable value is assigned to these parameters.

There is no significant change in the parameters' sensitivities across the geometrical shapes. Therefore, the results of the sensitivity analysis can be generalised for multi-LOD approach to determine which information best serves to reduce uncertainty in a model at an early stage of design. The parameter groups are divided into three levels, which causes more than 50%, 15% and 2% variation of response respectively, *i.e.* predicted energy consumption. The designers should prioritize finding a suitable value for geometrical parameters at the first level of multi-LOD as it causes most part of the uncertainty. In the next level, technical specifications and operational design parameters should be focussed. In the final stage, suitable values to be assigned to window construction and system efficiency parameters. The shape of the building also influences its energy performance but difficult to be quantified because of its categorical nature.

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*, infiltration and lighting and electrical heat gains which may not be possible to define in the range of ± 25% at an early stage of design. In that case, the method can be used to compute the uncertainty contribution and use the new findings to determine the information required at each level.

A typical office building in Munich as a test case has been examined in the research. The weather plays a significant role in energy predictions and affects the parameters' sensitivities; thus, the results are cannot be generalised for another location without further tests. The different building shapes of the comparable area with varying length and width have been included in the analysis to make the sensitivity analysis results still more generalisable for the early stage of design. The parameter space is varying only ± 25% from the mean values for most of the parameters, and the sensitivity analysis results are only applicable in the defined range. The building energy model considers the effect of self-shading only. The effect of shading from the surroundings or overhangs is not studied in this research, which is expected to influence the energy prediction. As the focus of the paper is to study the early stage building energy models, the building system is represented in a simplified way by efficiency parameters only. The presented approach is of mono-disciplinary nature, *i.e.* the decision-making for an energy-efficient design while the building design process is of collaborative nature, which involves several different disciplines. There are possibilities that some other design parameters are important, or the parameters have conflicting influences on the performance prediction involving multiple disciplines. This issue can be resolved using the weighted-sum method or focussing all the important parameters for each discipline per LOD.

## 6. Conclusions

The ranking of design parameters based on their influence on energy prediction is useful for the development of information requirements in a multi-LOD approach from an energy-efficiency perspective. There is very little change in the sensitivities of design parameters across different building shapes and no change in the ranking of highly influential parameters. Thus, it is concluded that there is no variation in the ranking of design parameters in the building energy models at an early stage of design. The uncertainty contribution by a group of parameters is more relevant for the identification of required information at each level. It is possible to identify three levels in the uncertainty contribution by the group of parameters corresponding to the three levels of multi-LOD approach. In a typical multi-LOD approach, a designer shall start the design process with a rough definition of all the design parameters, *i.e.* defining parameters with a mean value and range of ± 25%. Afterwards, the designer should focus on the design parameters in the following order of preference – geometrical parameters (Level 1), technical specifications and operational design parameters (Level 2), and window construction and system efficiency parameters (Level 3). Furthermore, it should be noted that energy performance is also influenced by the building shape and finding an optimal shape should be of primary importance at the beginning of the design process.

The sensitivity analysis of the energy model is useful to identify the most relevant design parameters for performance-based design. The parameters are grouped based on their nature to ascertain uncertainty caused by a group of parameters. The group of parameters causing maximum uncertainty are identified and ranked using the approach of sensitivity analysis. The parameter groups should be focussed in the order of their preference in a multi-LOD approach to allow more accurate prediction of energy as the design progresses.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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