MASTER

Enhancing design support of zero energy buildings by using sensitivity analysis and visualisation methods

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by using sensitivity analysis and visualisation methods

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Preface

This is the graduation research for the master track building Physics and Services of the faculty of Architecture, Building and Planning at the Eindhoven University of Technology.

I would like to thank my supervisors who guided me during this part of the project: prof.dr.ir. J.L.M. Hensen and dr.ir. P. Hoes. With a special thanks to R.R. Kotireddy who guided me through the project and for his helpful advice, J van der Kamp who guided me at Kuijpers installations and my fellow students for the feedback during the progress meetings and beyond.

Also, I would like to thank my friends and family who supported me during this process. It was not easy but partly by their support I finished this research.

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Robert Snoeren

Abstract

In the coming years, all new buildings should be nearly zero-energy buildings to reduce the total energy consumption. The design of nearly zero-energy buildings is a complex process. It involves optimisation and consideration of, and understanding the interaction between different design parameters and operational scenarios yet, it is of great interest for designing and can enhance the design decision-making process. The interaction between different design parameters can be investigated using different sensitivity analysis methods, such as local sensitivity analysis method which focuses on one parameter at the time where global sensitivity analysis methods focus at multiple or all parameters simultaneously. All these methods can eventually be divided into sub-methods, for example, the screening-based method and the variance-based method. To enhance the design decision-making process, the implementation of visualisation methods is a fast and easy way of converting data and in this case, the outcomes of the results of simulations and the sensitivity analysis.

This research presents a method of investigating the influence and interactions of different design parameters and operational scenarios on different performance indicators. At first, the most suitable sensitivity analysis and visualisation methods are selected which are applied on a case study. Based on the results, a tool is developed to visualise the most influential parameter and the interactions between different parameters to enhance the design decision-making process.

Based on literature review, the variance-based sensitivity analysis is found to be the most appropriate method for identifying the influences and the interactions between parameters. The variance-based sensitivity analysis can take several design parameters into account including the scale and shape, as well as the interaction between the different parameters. These outcomes are visualised in several visualisation schemes such as bar plots, parallel coordinate plots and scatterplots. For this research, a stakeholder has advised about his preferences when using this tool as well for defining the different design parameters, operational scenarios and performance indicators. The selected sensitivity analysis method is applied to the outcomes of the simulation results and visualised in the visualisation tool. The applied sensitivity analysis identifies the most influential parameters of the different performance indicators. It is found that infiltration rate is the most influential parameter on heating demand and overheating hours. Similarly, thermal resistance, PV panel size and the window-to-wall ratio has the most influence on the total cost of ownership.

The interactions between different design and operational parameters and their corresponding influence on preferred performance indicators are communicated to stakeholder using visualisation methods to enhance design decision-making process. Different visualisation methods such as parallel coordinates plot, bar plot and scatter plot are compared. Based on discussion with stakeholder, it is found that the use of a 3D-scatterplot is much more user-friendly and easier to understand. To define the direction of the influences, scatterplots are implemented in the visualisation tool. Overall, the visualisation tool in combination with the used methods is an easy to understand for stakeholder that captures the essence of defining the influences and interactions between parameters. To improve the use of the tool, adjustments can be considered in connecting different or multiple building performance simulation tools as well implementing the possibility of connecting the building geometry in the visualisation tool. At last, going more into detail regards parameter chose, changes in the building design, and selecting specific sections for calculations would be an improvement of the tool.

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1 Introduction

1.1 Problem statement

The building sector represents between 30% and 40% of the total energy consumption in the most developed countries as shown in Figure 1.1 [1][2]. Reducing the total energy consumption, will reduce the environmental impacts such as global warming, climate change, and ozone layer depletion [3]. Therefore, the Energy Performance of Buildings Directive (EPBD) has stated that all new buildings should be nearly zero energy buildings (nZEB) by 2020 and all public buildings by 2018. [4]. The design of zero energy buildings is a complex process [5]–[9]. It involves optimisation and consideration of multiple design parameters and operational scenarios as shown in Figure 1.2 [5][10]. However, analysing the influence of a design parameter in a traditional approach, most of the time impact of one variable at a time is investigated [7], [9]. [O'Brien et al., 2011] has stated that it would be unwise to only investigate one variable at a time because of the interaction between different design parameters and thus, they investigated multiple methods of sensitivity analysis to identify the interaction between different design parameters. To determine the most influential parameter they used a local sensitivity analysis. For determining the interaction, they used a global sensitivity analysis method [5].

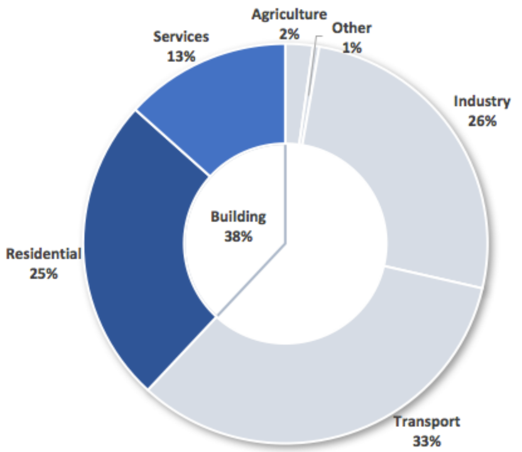

Figure 1.1 2014 Energy consumption by sector in the EU-28

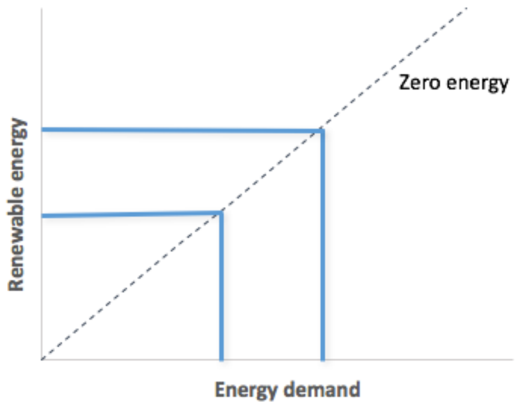

Figure 1.2 Optimisation to achieve zero energy [10]

Understanding the interaction between the different design parameters is of great interest for designing and can enhance the design decision-making process. For example, [Sun, 2014] has applied a cost optimised approach to minimise the overall cost of renewable energy systems by evaluating the impact of each parameter by using differential sensitivity analysis [5]. [Attia et al, 2012] developed a decision support tool to enhance the design decision-making process in the early stage of a net, or nearly zero energy buildings design. Participants, in the investigation of Attia et al., who have used the tool, operated their design more from an informative decision support.

The used sensitivity analysis in the decision support tool focus on a single parameter and its consequences on energy saving [7]. Furthermore, in the design phase, most of the operational scenarios are fixed in simulations and their impact, in combination with design parameters, on overall performance are rarely addressed. Although several studies focus on the interaction of different parameters on performance indicators, the interaction between the different parameters is mostly neglected [5]. Determining the most influential parameter, a decision-maker can use this parameter to optimise the building design. By considering the interactions between different parameters, a decision-maker can identify the importance between different parameters. For example, the interaction between window-to-wall ratio and the thermal resistance of the glass. A small window-to-wall ratio could suggest that the thermal mass won't have much influence. However, when increasing the window-to-wall ratio the importance of the thermal resistance of the glass will increase [5].

The tool of data visualisation improves processing a large amount of data. Data visualisation is fast and an easy way of converting data, where experiments with different parameters, can be performed easily. By using data visualisation schemes areas of improvements can be easily detected, as well as influence factors [11].

Hence, in this work, sensitivity analysis is carried out to investigate the interactions between different design parameters. Using this method, designer/decision-maker can identify the most influential parameters that define the building performance and visualisation methods will be presented for stakeholders to enhance design decision-making process.

1.2 Research goal & objectives

1.2.1 Aim

The aim of this research is to enhance the design decision-making process by investigating the influence and interactions of different design parameters and operational scenarios on different performance indicators, and visualise these results to enhance communication.

1.2.2 Objectives

To reach the goal of this project, the following research objectives have been established.

1) Developing a method/ tool which shows different visualisation methods in such way that, it enhances the design decision-making process.
    a) Defining the most appropriate sensitivity analysis method to define the most influential design parameter, and to define the interactions between these parameters.
    b) Defining the most appropriate visualisation method to demonstrate the outcome of the sensitivity analysis.
    c) Asses the suitability and usability of the chosen sensitivity analysis method and visualisation methods with stakeholder.

1.3 Outline

This research is divided into several parts. At first, literature study has been conducted to investigate different methods of sensitivity analysis as well as different visualisation methods. Next, a stakeholder has been selected followed by defining different design parameters, scenarios based on building operational scenarios and the most important performance indicators. The next step is, to assess the performance of the design space for scenarios using building performance simulations. On the results, the selected sensitivity analysis method will be applied to investigate the impact of the design parameters on the performance indicators and between each other. These results will be presented in visualisation schemes with the aim to enhance the design-making process.

2 Literature study

Different sensitivity analyses methods used in the building performance context are reviewed and the most suitable method is selected. Similarly, suitable visualisation methods are identified, based on literature review, for visualisation of the outcome of sensitivity analysis to stakeholders to enhance the design decision-making process.

2.1 Sensitivity analysis

Sensitivity analysis is the investigation of the influence in the model outputs which can be assigned to different origins of influences of the model input [12]. The use of sensitivity analysis has a very wide range and it can be divided into four main groups [13]:

- Decision making or development of recommendations for decision makers;
  For instance, identifying critical values, identifying sensitive or important variables, comparing the values of simple and complex decision strategies
- Communication;
  Making recommendations more credible, understandable or persuasive and allowing decision-makers to select assumptions
- Increased understanding or quantification of the system;
  Estimating and/ or understanding relationships between input and output variables
- Model development;
  Calibrating, simplifying, or Testing the model for validity or accuracy.

For this research, the main-focus will be identifying critical values, estimating and understanding relationships between input and output variables, and making recommendations more credible.

There are different methods to perform sensitivity analysis which can be distinguished in local sensitivity analysis and global sensitivity analysis. Local sensitivity analysis focuses at one parameter at the time where global sensitivity analysis focuses on all parameters simultaneously.

2.1.1 Local sensitivity analysis

Local sensitivity analysis consists of changing one input value for each simulation, where the remaining input values stay fixed. Therefore, changes in the outputs are a direct result of the change made in the single input. To determine the individual effects, the following equation can be used [14]:

$$\Delta p_i = p_i - p_B \qquad \text{Equation 2.1}$$

Δp_i = Individual effect
p_i = Value predicted using modified value of input i
p_B = Value predicted using base-case inputs

Advantage

The advantage of using the local sensitivity analysis method is that it is fast and straightforward because few simulations are needed. Also, local sensitivity analysis works well with linear models.

Disadvantage

The disadvantage of using Local sensitivity analysis is that it only investigates a few input values. Also, self-verification in this method is not possible. At last, the interactions between the input values cannot be considered although, it is possible to identify the most influential input values according to [15]–[17].

In [Lu et al, 2015] they used differential sensitivity analysis named one-way sensitivity analysis to assess the impacts of changes in certain input variables. Here they investigated one parameter at the time by changing the input value with ±20% and investigated the changed outputs based on several performance indicators to identify the most influential parameter by comparing the percentage of variance. [Lu et al, 2015] not only performed one-way sensitivity analysis but as well two-way and multiway sensitivity analysis. Here they compared the percentage of variance of several outcomes of several simulations what has been performed to investigate the influence [17].

[O'Brien et al, 2011] states that it would be unwise to optimise only one design parameter at a time because of the interaction between different parameters. The interaction between design parameters is investigated by examining the deviation between the minimum and maximum value of two different design parameters. The change in slope quantifies the interaction between the design parameters. For instance, the higher the deviation in slopes, the more the interaction between the variants and vice-versa, as can been observed in Figure 2.1 and Figure 2.2 [5].

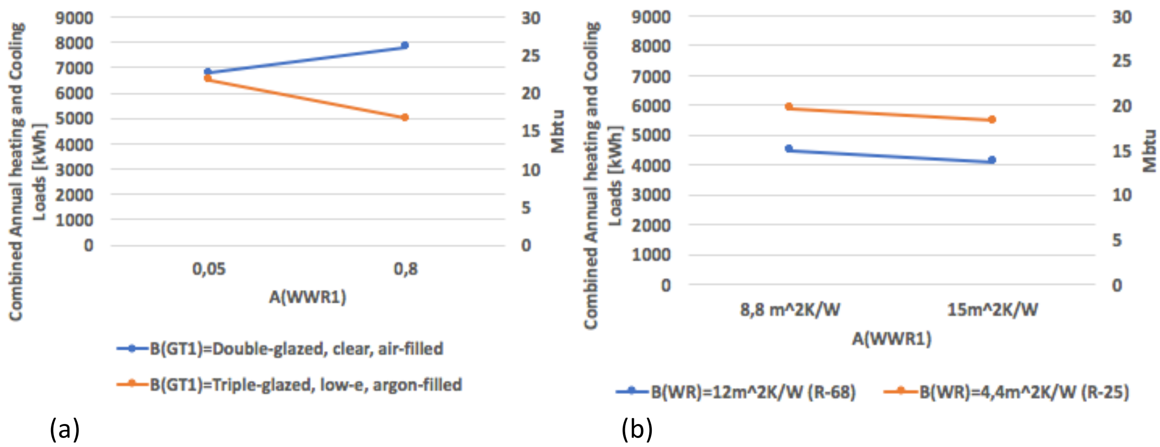

Figure 2.1 Example local sensitivity analysis showing interaction plots where: (a) shows a strong interaction and (b) shows a weak interaction [5]

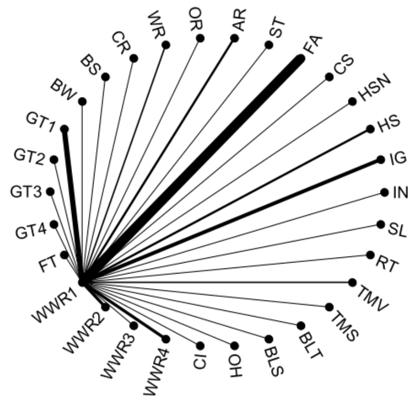

Figure 2.2 Visualisation of the interactions between different parameters [5]

2.1.2 Global sensitivity analysis

Global sensitivity analysis is mostly used to define the influences of parameters based on all input values [18]. There are different methods to perform global sensitivity analysis. In this research, the following methods will be distinguished: Regression method, Screening-based method and variance-based method.

2.1.2.1 *Regression method*

According to the investigation of [Tian, 2012] on sensitivity analysis methods, the most commonly used sensitivity analysis in building energy analysis is the regression method [18]. Regression analysis has three major functions.

1. Description of the relation between parameters
2. Control of predictor parameters for a given value of a response parameter
3. Prediction of a response based on predictor parameters

To easily understand the outcome many indicators can be used. Although, first the relation between inputs and output should be identified, like using the Monte Carlo analysis. These indicators could be; the Standardised Regression Coefficients (SRC), Partial Correlation Coefficient (PCC) and their rank transformation; Standardised Rank Regression Coefficient (SRRC) and Partial Rank Correlation Coefficient (PRCC) [16], [18].

Advantage

The advantage of using regression analysis is, that it allows sensitivity evaluation of individual model inputs with respect to the simultaneous impact of other model inputs on the results. Other techniques can evaluate the unique contribution of a model input with respect to variation in a selected model output. By using Rank regression, it is possible to capture monotonic relationships between input and output, also in a nonlinear situation [16].

Disadvantage

The drawback of regression analysis is, when the expectations of regression are not met, it results in a possible absence of robustness and also that there must be a functional form for the interaction between the output and the selected inputs. This results that the regression analysis, in this case, does not have a strict quantitative interpretation [16].

2.1.2.2 *Screening-based method*

The goal of the screening method is mostly to identify some input factors from a large group of factors, without reducing the output variance. The Morris method is the most used screening method in building performance analysis according to [Tian, 2012]. The results of the Morris analysis mostly are shown in a graph where the mean value of the calculated effect (μ) is compared with the standard deviation of the effect (σ). One high mean value results in a big sensitivity; small mean value results in low sensitivity [15], [18], [19].
In the Morris method, the input parameters are calculated by using the elementary effect as given in Equation 2.2

The elementary effect is a traditional One-At-the-Time sensitivity analysis method.

$$EE_i(X) = [y(x_1, x_2, \dots, x_{i-1}, x_i + \Delta, x_{i+1}, \dots, x_k) - y(x)]/\Delta \qquad \text{Equation 2.2}$$

Here the Δ determines the magnitude of steps also known as the resolution of sampling [20].

The mean and standard deviation as proposed by Morris (1991) can be calculated by the following equations [20][21]:

$$\mu_i = \frac{\sum_{n=1}^{r} EE_n}{r} \qquad \text{Equation 2.3}$$

Standard deviation

$$\sigma_i = \sqrt{\frac{1}{r}(EE_n - \mu_i)^2} \qquad \text{Equation 2.4}$$

To detect input factors with an important overall influence on the output the following formula can be used [20]:

$$\mu_i^* = \frac{\sum_{n=1}^{r} |EE_n|}{r} \qquad \text{Equation 2.5}$$

Advantage
The main advantage of using a screening-based method is that the computational cost is low compared with other global methods. It can also distinguish linear input values from nonlinear input values [15], [18].

Disadvantage
A drawback of the screening-based method is that it does not allow uncertainty analysis as this method tries to provide qualitative measures by ranking input factors, but it is not able to quantify the effect of different factors on outcomes [15], [18].

2.1.2.3 *Variance-based method*

The variance-based method is used to determine the statistical corporation between an output (response variable) and one or more input (factors). Single-factors variance-based method is used to investigate the effect of one factor on the response variable. Multifactor variance-base method deals with two or more factors and it is used to determine the effect of interactions between factors [16]. The variance-based method is suitable for complex non-linear and non-additive models. It can quantify all the variance of the response variable due to every factor also it considers the interaction effects among variables [18]. For non-linear, non-monotonic problems the Fourier Amplitude Sensitivity Test (FAST) could be used. It estimates the expected value and the variance of a model prediction by performing numerical calculations [15]. Another method is Sobol's method, it is one of the most powerful techniques of global sensitivity analysis. The Sobol method determines the influence of each input parameter and their interactions to the overall model output variance [22].
The Sobol method determines the first order sensitivity index and total effect index. The first order sensitivity index determines the main effect output variance of an input parameter, where the total effect index indicates the sum of the first order sensitivity index, second order sensitivity index, and so on [23]. Although each order can be calculated, it is generally accepted to determine only the first order sensitivity index and the total effect index [24].

The Sobol method is calculated with the following formulas [23]:
In the following formula, the input parameters (X_1, X_2, X_3,…, X_n) are a function of model output (Y) what results in:

$$Y = f(X_1, X_2, X_3, \dots, X_n) \qquad \text{Equation 2.6}$$

the total variance is calculated with:

$$V(Y) = \sum_i^q V_i + \sum_i^q \sum_{i>j}^q V_{ij} + \cdots + V_{12\dots q} \qquad \text{Equation 2.7}$$

$V(Y)$ = total variance
$\sum_i^q V_i$ = Sum of Partial variances
$\sum_i^q \sum_{i>j}^q V_{ij}$= Includes all the partial variances of the interaction of two input parameters

The first order sensitivity index is calculated with:

$$S_{k,\dots} = \frac{V_{k,\dots}}{V(Y)} \quad \text{Equation 2.8}$$

where:
V_i= variance of design parameter X_i
$V(Y)$= Total variance of all design parameters ($\sum X_i$)

And the total effect index:

$$S_{T_i} = S_i + \sum_{i \neq j} S_{ij} + \sum_{i \neq j \neq l} S_{ijl} + \cdots \quad \text{Equation 2.9}$$

Advantage
The advantage of using the variance-based method is that it can quantify all the variance of the response variable due to factor and it can also consider the interaction effects among variables [3, 6]. The FAST method has the advantage that it is a global method, but with little adjustments, it can be used as a local method as well. It also allows large numbers of variations in the input factors [15].

Disadvantage
The disadvantage of using variance-based method is that it requires a lot of simulation runs resulting in a high computational cost [15], [16], [18].

2.1.3 Overview of sensitivity analysis methods

Table 2.1 gives an overview of the different properties, the different methods of sensitivity analysis and if these properties can be reached by the specific methods. In this project, we define the following selection criteria:

1. Taking all parameters into account simultaneously
2. Is the method is suited for non-linear input and output data
3. Taking the scale and shape of the input parameter into account
4. Attribute the variance of a model output to each parameter
5. The method show the interaction effects on the sensitivity between parameters

Based on the first two requirements the screening-based sensitivity analysis and the variance-based sensitivity analysis are the two most promising methods. [Kristensen et al. 2016] and [Wu et al, 2013] investigated the differences between the Morris method (screening-based) and the Sobol method (variance-based). The big differences between these methods are, that the Morris method is not able to take the scale and shape of input parameter distributions into account, also it cannot attribute the variance of a model to the output. At last the Morris method cannot show the interaction between the sensitivity of different parameters. All these points are possible with Sobol's method. A drawback of Sobol's method is that it has a high relative computational cost [25][26]. The goal of this research is to show not only the most influential parameter but as well the interaction between different parameters. Therefore, the most suitable sensitivity analysis method for this research is variance-based sensitivity analysis method.

Table 2.1 Properties and methods of sensitivity analysis

	Local	Global		
		Regression	Screening	Variance
Taking all parameters into account simultaneously	No	Yes	Yes	Yes
Usable for non-linear data	No	Most linear	Yes	Yes
Taking the scale and shape of the input parameter into account	No	No	No	yes
Rank the importance of the parameters	Yes	Yes	yes	yes
Attribute the variance of a model output to each parameter	No	No	No	Yes
Can the method show the interaction effects on the sensitivity between parameters	Yes	No	No	Yes
Easy to carry out	Easy	Easy	Medium	Difficult
Relative computational cost	Low	Low	Medium	high

2.2 Visualisation methods

To enhance the design decision-making process different visualisation methods has been used. There are several methods and techniques to enhance data in visualisation scheme's each with its own specific characteristics. The most common known visualisation methods and techniques are [27]:

- Cladogram
- Dendrogram
- Information visualisation reference model
- Graph drawing
- Heat map
- Hyperbolic tree
- Multidimensional scaling
- Parallel coordinates
- Problem-solving environment
- Tree mapping

Table 2.2 gives an overview of the criteria for the visualisation methods of this project. Some of the methods/ techniques can be subdivided into different types of plots, diagram and mappings. In building performance simulations, these methods/ techniques are not all of interest. Hierarchical data visualisation schemes, for instance, are not common in BPS that excludes; cladogram, dendrogram, hyperbolic tree and tree mapping as shown in Table 2.2.

For this project, the visualisation schemes should be able to allow a quantitative comparison of the influence of the design parameters and operational scenarios as well as the comparison between the performance indicators.

Table 2.2 Properties and methods of visualization methods

	Cladogram	Dendrogram	Graph drawing	Heat map	Hyperbolic tree	Multidimensional scaling	Parallel coordinate	Tree mapping
Comparison of the influence of a parameter on a performance indicator	No	No	No	Yes	No	Yes	Yes	No
comparison of the influence between the parameters	No	No	Yes	Yes	Yes	Yes	Yes	No
Comparison between the performance indicators	No	No	No	Yes	No	Yes	Yes	No

Therefore, the most interesting visualisation methods are:

- Multidimensional scaling
  In multidimensional scaling, the similarity between individual input data's is compared [28]. For sensitivity analysis, there are many possibilities to present the results for instance: scatter plot, which shows mostly two variables for a set of data; Box plot, which shows different groups of data based on their quartiles; tornado plot and spider plot.
- Parallel coordinates
  The parallel coordinates plots are mostly used to visualise high dimensional data, where each observation is based on its coordinate value set out against their coordinate indicator [29]. Figure 2.3 shows a parallel coordinate plot that presents the configurations and the resulting performance of all studied design objectives as used in [Lee, 2014].
- Heat mapping
  In heat mapping, the values are represented as colours. Figure 2.4 shows an example of heat mapping in combination with a scatter plot. Here [Lee et al, 2015] compared the net carbon emission against the annualised relative cash flow in a scatter plot and showed the annual energy consumption by using "heat mapping".

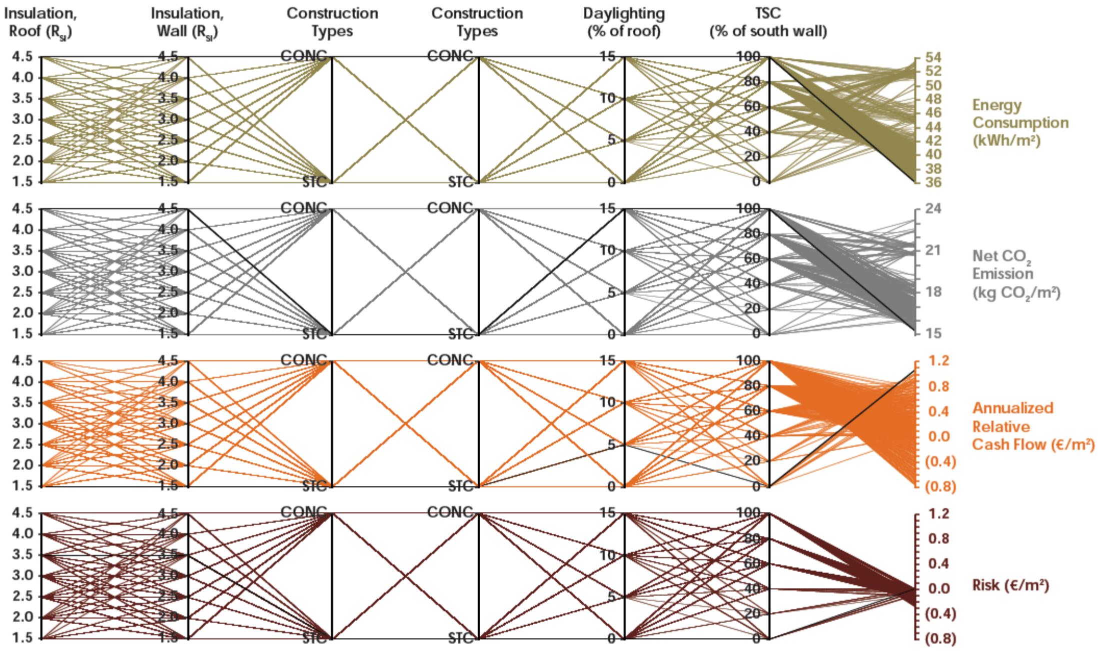

Figure 2.3 Example of parallel coordinate plot used in [Lee, 2014]

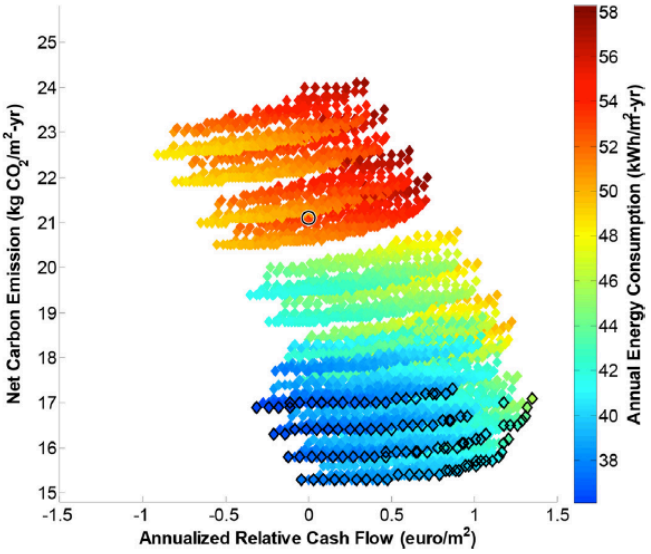

Figure 2.4 Example of a scatter plot in combination with heat mapping [30]

3 Methodology

In this chapter, a description is given of the methodology of the project. A description is given on which steps have been taken to answer the different objectives to answer the main question.

3.1 Project methodology

The methodology of this project is displayed in a flowchart as shown in Figure 3.1. At first, literature study has been conducted to investigate different types of sensitivity analysis methods and visualisation methods. The most suitable sensitivity analysis and visualisation method will be picked to identify the most influential parameters and the interaction between the different parameters. Based on a chosen stakeholder, design parameters, operational scenarios and performance indicators will be selected which will be applied on a case-study. This case-study will be based on a reference building and simulated with a building performance simulation tool. The different design parameters and operations parameters will be simulated, followed by applying the chosen sensitivity analysis method and visualisation schemes. The results will be discussed with the stakeholder if they can identify the most influential parameters, the interaction between parameters and if the visualisation method enhances the design decision-making process.

In short:

1. Select a decision maker/ stakeholder and define the following parameters based on decision maker's preferences
    - Define design parameters
    - Define scenarios based on building operational scenarios
    - Define performance indicators

2. Investigate sensitivity analysis methods used in building performance context/other fields and identify a suitable method in the present context.
3. Investigate visualisation methods used in building performance context/other fields and identify suitable methods relevant in the present context.
4. Assess the performance of design space for the scenarios using building performance simulations.
5. Assess the impact of the design parameters and operational scenarios on performance indicators, presented in proper visualisation schemes

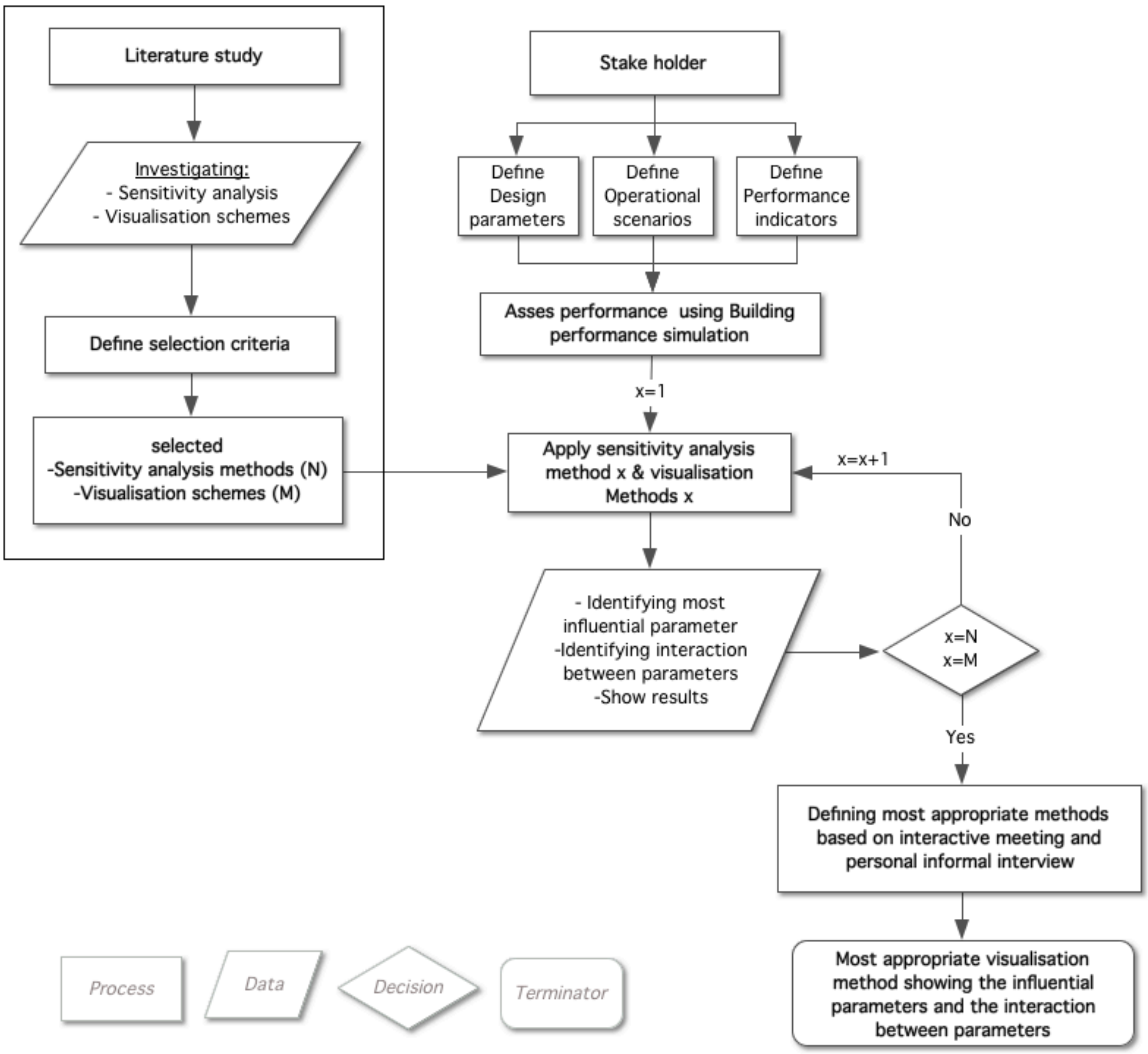

Figure 3.1 Flowchart of finding the most appropriate sensitivity analysis and visualisation method for a certain stakeholder

3.2 Calculation methodology

In this research, the input values will be based on the design of experiment approach. For this research, the operational scenarios and the design parameters will be analysed separately. To merely analyse the most influential design parameters and the interaction between these variants the mean value of all the operational scenarios is taken. The same is done for the analysis of the most influential operational scenario, where the mean value is taken over all design parameters. This results in a generalised building design, to cancel the influence of the design parameters and merely focus on the operational scenarios. A schematic overview of this process can be seen in Figure 3.2.

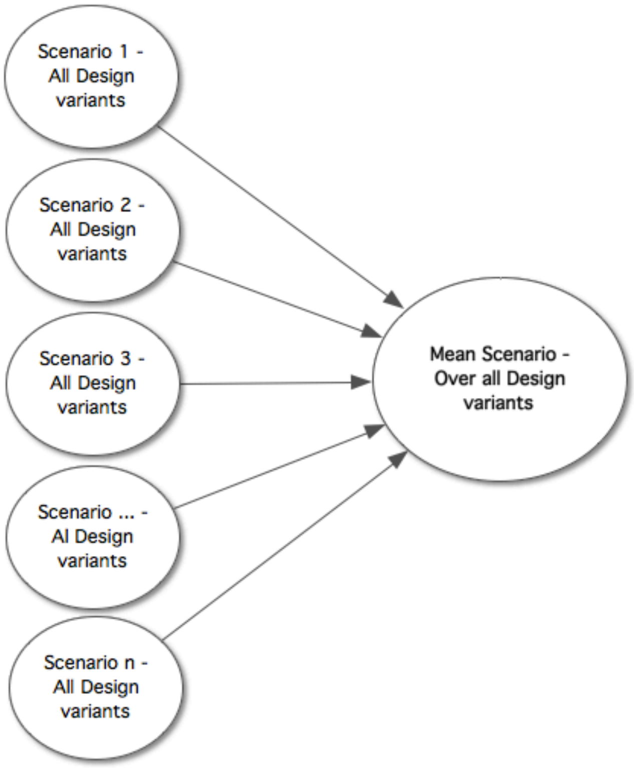

Figure 3.2 Schematic overview of creating the mean scenario. Here the mean value of the different operational scenarios is taken over all design parameters.

To identify the most influential parameter and the interaction between the different parameters the variance-based sensitivity analysis method has been used. The identification of the most influential parameter is calculated with a one-dimensional sensitivity analysis, and the interaction between the different parameters is calculated with a multidimensional sensitivity analysis.

3.2.1 Most influential parameter

The most influential parameter is determined by calculating the percentage of the variance of each parameter. To determine the influence of each parameter the Pooled variance has been used which calculates the variance of the difference [appendix A]. The variance of a parameter is calculated over all outputs of a specific performance indicator. Here all outputs of the investigated parameters are pooled for the different input values of this parameter where the remaining parameters have fixed values. A schematic overview of this pooled variance can be found in Figure 3.3. At the end, over all the pooled variances the variance is calculated for the parameter. With these variances, the most influential parameter can be determined by using $S_{k,\dots} = \frac{V_{k,\dots}}{V(Y)}$ Equation 2.8. Figure 3.3 gives a schematic overview of how to determine the most influential parameter.

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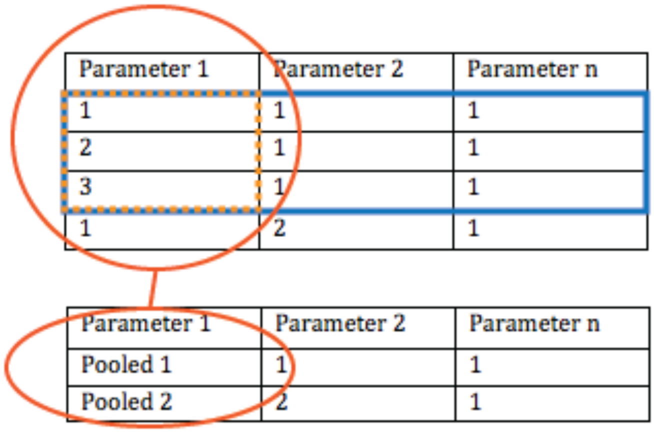

Figure 3.3 Schematic representation of the pooled variance over variables 1,2,3 of parameter 1.

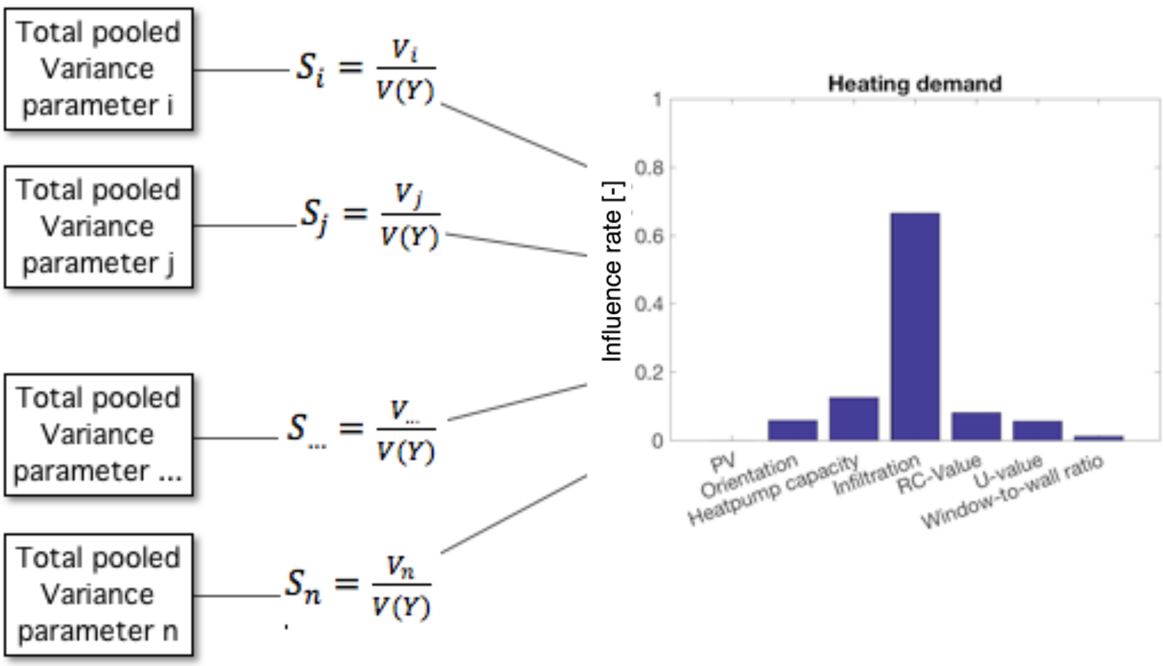

Figure 3.4 Schematic overview of identifying the most influential parameter. Here the percentage is calculated over the pooled variance of each individual parameter to generate the bar plot with the most influential parameter.

3.2.2 Interaction between parameters

For the interaction between different parameters the pooled variance is used again. Figure 3.5 gives a schematic overview of how to calculate the interaction between the different parameters. Here one parameter (k) is pooled where then the variance is calculated over all the variances of the different input values of one parameter(i). For these variances, $S_{k,\dots} = \frac{V_{k,\dots}}{V(Y)}$

Equation 2.8 is used again to calculate the percentage of the influence. The outcome is given in a bar plot. The height of the bars identifies which parameter has the most interaction with parameter k.

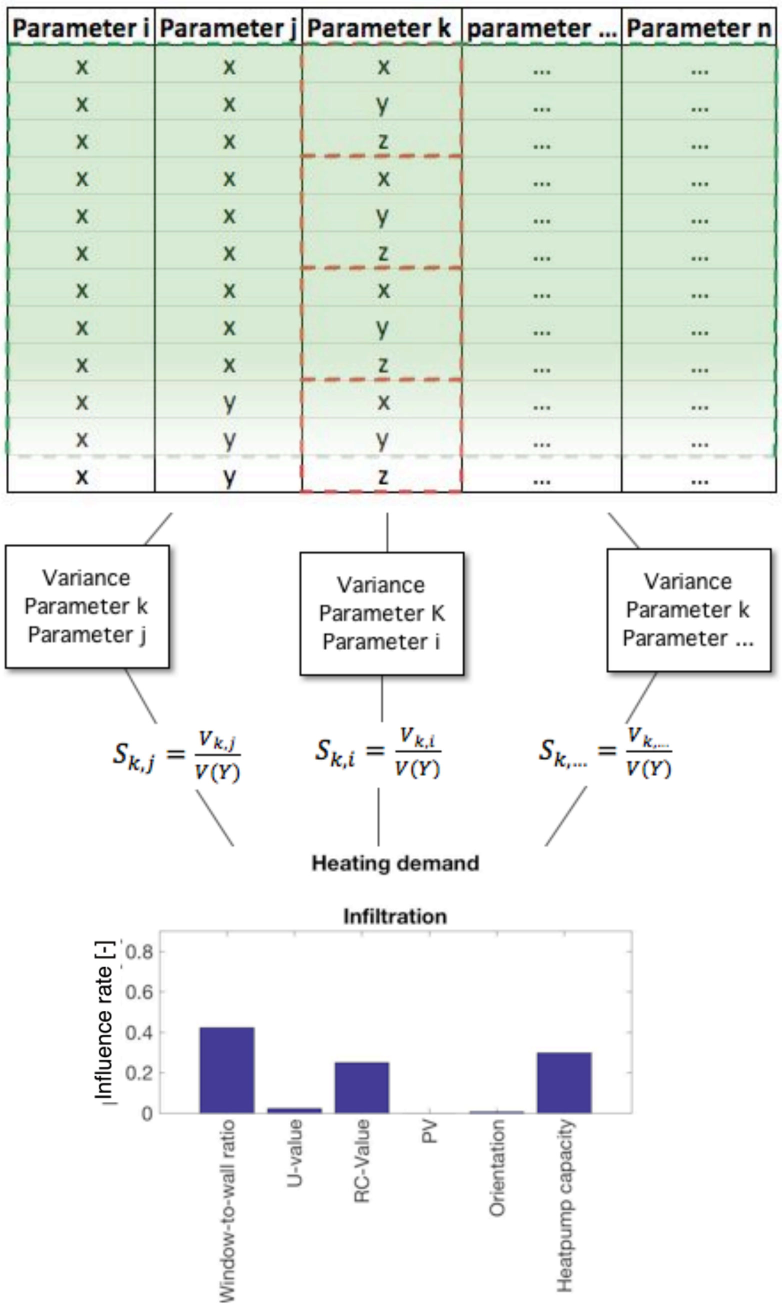

Figure 3.5 Schematic overview of determining the interaction between one parameter and all other parameters. Here the percentage between the pooled variance and one value of another parameter is calculated and visualised in a bar plot.

To give a more insight of the interaction between the two parameters described earlier, the most influential combination between these two parameters, can be determined. Figure 3.6 gives a schematic overview of how to calculate this influence. Here the variance is calculated for one input value of a parameter(i_x) with one input value of another parameter (j_x). For these variances, $S_{k,...} = \frac{V_{k,...}}{V(Y)}$ Equation 2.8 is used again to calculate the percentage of the influence. The outcome is given in a bar plot. The most influential combination is in this case defined by the height of the bars. This means that the highest bar has the most influence on the performance indicator.

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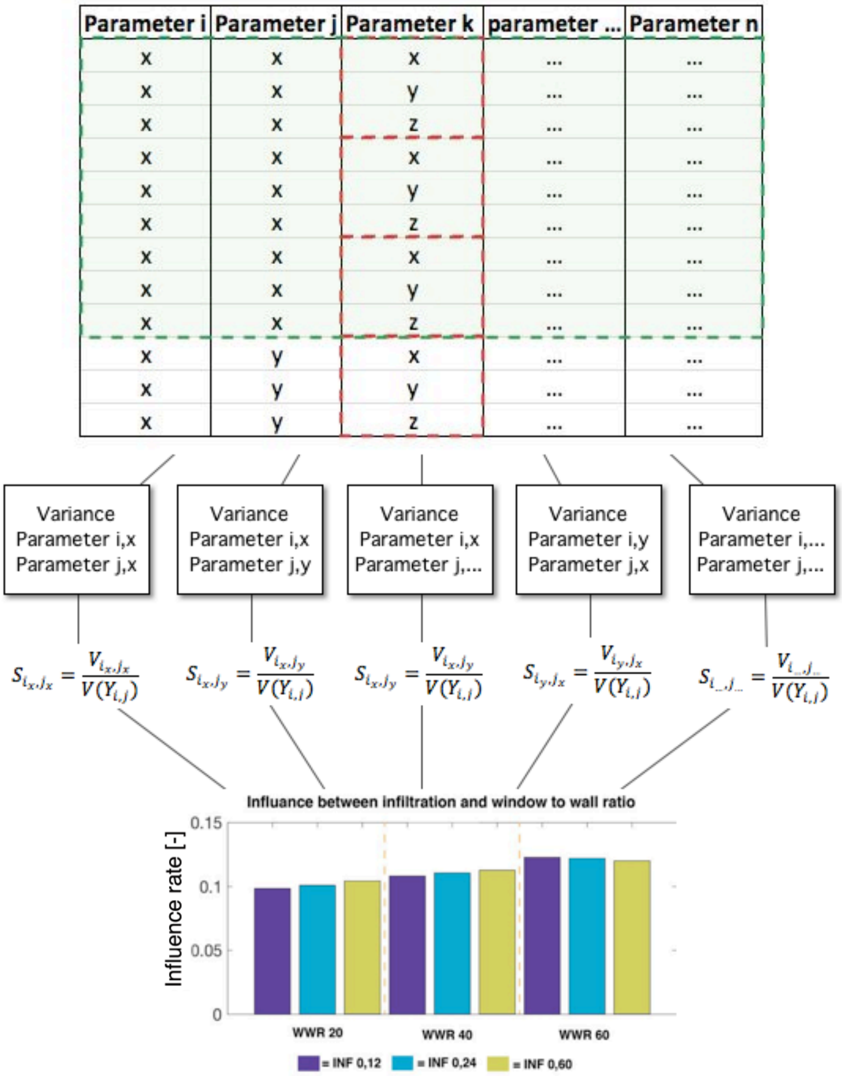

Figure 3.6 Schematic overview of determining the most influential combination between two parameters. Here the percentage is calculated over the variance of parameter i_x and j_x, ix and j_y, and so on.

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3.2.3 Parallel coordinate plot

The most influential parameters are first visualised in bar plots as can be seen in Figure 3.4. To improve the design decision-making process the interaction of a parameter, and the interaction between different parameters can be shown in one figure by using the parallel coordinate plot.

Figure 3.7 shows the outline how the parallel coordinate plot has been set up. As can be seen in Figure 3.7a, the parallel coordinate plot is based on the most influential parameter. By investigating each value of a parameter individually Figure 3.7b can be made. This parallel coordinate plot shows the most influential parameter based on the increase/ decrease of a specific parameter. By taking one input value of one parameter and one input parameter of another parameter, as done before with the multidimensional sensitivity analysis, Figure 3.7c can be created. This parallel coordinate plot shows the most influential parameter based on the variation of one parameter in combination with the variation of another parameter. With this plot, the influence of the most influential parameter can be visualised based on the interaction between different parameters.

For all figures, bar plots and parallel coordinate plots, which shows the most influential parameter or the interaction between different parameters, are quantified by the influence rate. This influence rate is the percentage of all variance considered and has a scale of 0 to1. This means the more parameters or input values are considered, the lower the number. However, the highest value represents the most influential parameter or interaction between parameter.

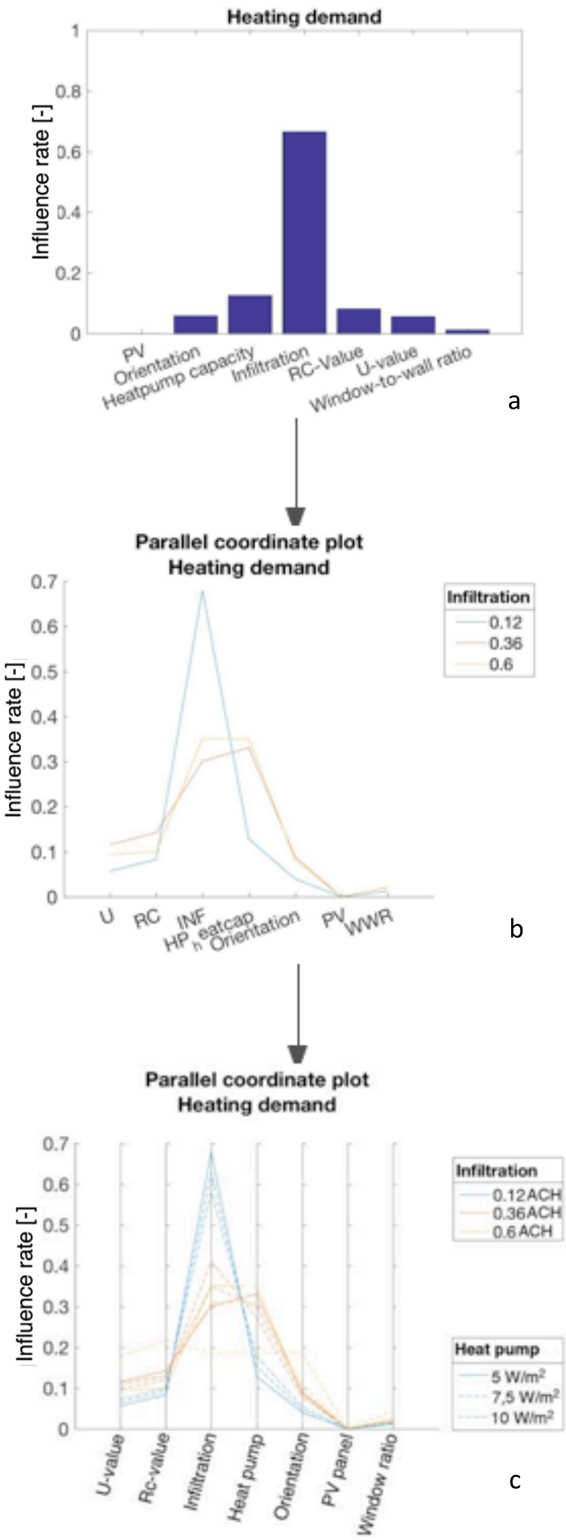


Figure 3.7 Set-up of converting the bar plot of the most influential parameter to a parallel coordinate plot including changes in parameters

3.3 The simulation tool

3.3.1 TRNSYS

TRNSYS is used for simulating performance of all designs across considered scenarios. In TRNSYS, the building is described in the type 56 component. A schematic overview of the model can be seen in Figure 3.8 and appendix B where in the appendix the different variables are given. As can been seen the external components are:

- Heat pump in combination with a storage tank and floor heating.
- Occupancy profile which is connected to the thermostat, and the internal heating gain in the building itself.
- Heat recovery system
- Natural ventilation
- Solar shading
- PV panel

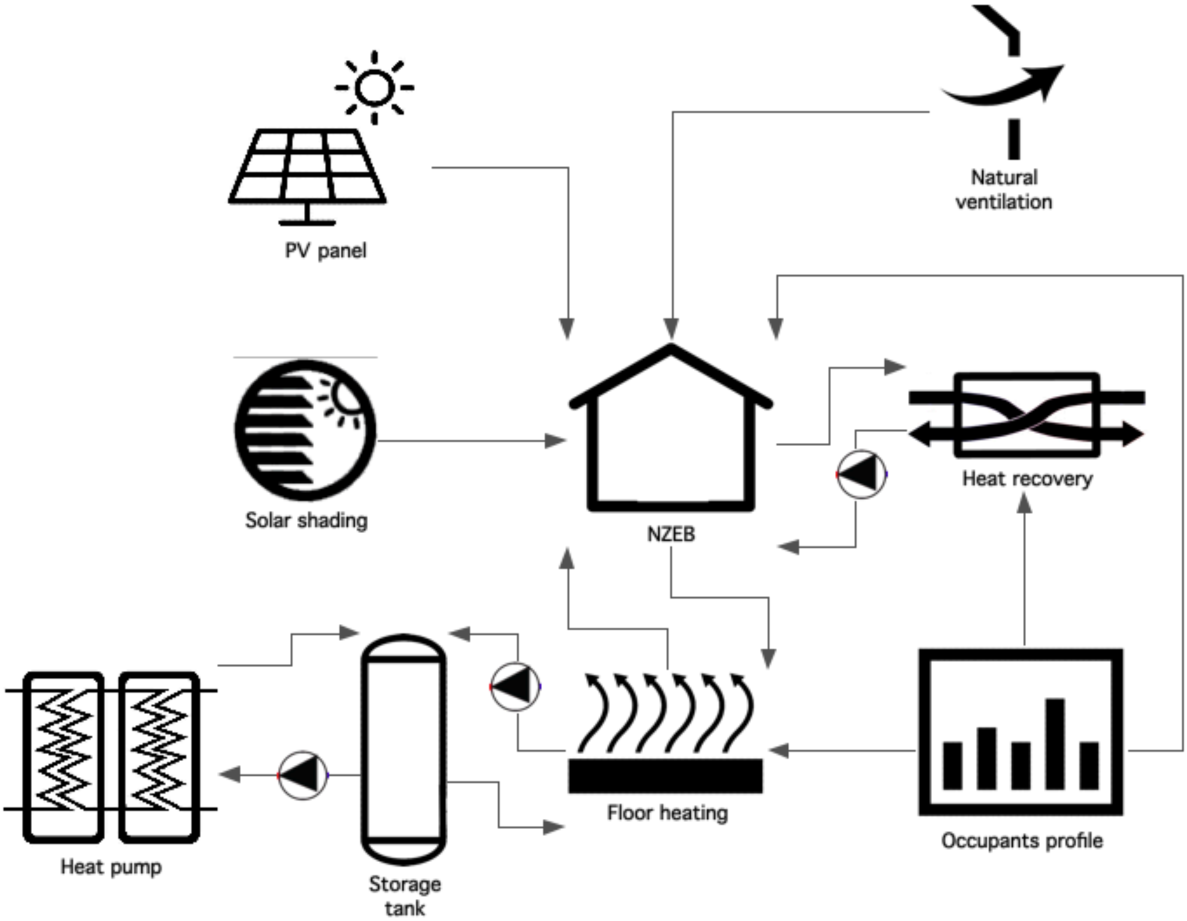


Figure 3.8 Schematic overview of the case-study building model.

3.3.2 Matlab

Matlab is used in general for visualisation and numerical computation [31], as well for analysing data, scientific and engineering graphics, modelling, simulation and prototyping [32]. In this project, Matlab is used for modeling an automatic process of running TRNSYS. In each simulation, one parameter is changed by Matlab where after each simulation the data is saved. Second, Matlab is used for the calculations of the interactions between the different parameters, and to define the most influential parameter by using the variance-based sensitivity analysis method. The outcomes of these calculations are shown in visualisation schemes, which are integrated into Matlab. At last a GUI is built in Matlab. A GUI is a graphical user interface which provides point-and-click control of software applications [33]. This GUI will provide an overview of the most influential parameter for the operational scenarios and design parameters and the different interactions between different parameters. With the GUI the user can see the interaction and influence in an interactive way to understand the process. The user can predict as well what will happen when some parameters will change based on the visualisation schemes what can be seen in the GUI.

4 Case-study

In this chapter, the case study for this project is described. A description is given of the stakeholder, the building, different design parameters, operational scenarios and performance indicators.

4.1 Stakeholders

Each decision maker in the building industry requires specific building performance related aspects. For instance, homeowners would prefer buildings that are very comfortable with low or no operational costs and low additional investment costs. Where a building service company prefer a relatively low energy demand and low overheating hours [10].

For this project, Kuijpers installations is willing to advise as a stakeholder for this project. Kuijpers installations is a building services company in the Netherlands with about 950 employees. Kuijpers designs, builds and maintains technical installations in buildings and industry to contribute to a healthy working environment [34].

For a company like Kuijpers, it is the essence to identify the most suitable installation, with respect to different expectation scenarios. Also, an integral approach between the architect, building owner and Kuijpers is desired. The building design, government requirements, requirements from the owner and the required installations all have a direct impact on the performance indicators. The key performance indicators for Kuijpers are therefore project dependent. Kuijpers tries to find a balance between the building and the user for each project. Although each project is independent and has its own key performance indicators, the performance indicators, given in Table 4.1, are common for a building service company like Kuijpers.

Table 4.1 Most common performance indicators for Kuijpers.

Performance indicator
Heating demand
Cooling demand
Peak loads
Comfort
Installation cost
Total cost of ownership
Requirements architect

Based on these performance indicators, design parameters and operational scenarios are established. To identify the interaction between different design parameters and operational scenarios a design of experiment approach is used. For each variable, several steps are considered, and for each step, a simulation will be performed. This results in a total of 46656 simulations. Table 4.2 shows the different design parameters including the minimum and maximum input value, and the number of steps taken for each variant where Table 4.3 shows this for the different operational scenarios.

4.2 Case-study building

The used case-study building for this project is a Dutch terraced house that represents 36,5% of all new build dwellings in the Netherlands [35]. The case-study building is based on a terraced house as described in 'variant calculations for requirements of net zero energy buildings' commissioned by the ministry of the interior and Kingdom Relations [36].

The used geometric building shape of the case-study building is described in 'Agentschap NL referentiewoningen 2013' [37] where more space is reserved for installations. The case-study building has a used surface area of approximately 130 m^2 and a loss surface area of about 175 m^2. Living room and kitchen constitute the ground floor, three bedrooms on the first floor and an attic on the second floor. The south façade has a large window on the ground floor and all bedrooms have windows of the same size. The thermal resistance is set at 6 m^2K/W, U-value 0.86 W/m^2K and the infiltration at 0.08 ACH. A detailed description of the building and the installation requirements can be found in appendix C.

4.2.1 Design parameters

4.2.1.1 *Building properties*

The Dutch building regulation has stated that the thermal resistance of a building should be 6 m^2K/w [38]. To reduce heat losses in the building the thermal resistance could be increased. Passive buildings are highly insulated buildings which uses solar radiation and waste heat of the building optimally. The thermal resistance of passive buildings is approximately 10 m^2K/w, with highly insulated windows [39]. Therefore, the minimum value of the thermal resistance will be 6 m^2K/w and the maximum value will be 10 m^2K/w.

4.2.1.2 *Infiltration*

Three infiltration rates that represent airtight to leaky building envelopes are considered in this study. Infiltration rate is varied from 0.12ach [40] to 0.6ach [41]

4.2.1.3 *Installation*

The heating capacity and the heating power of the heat pump are variables based on the constant COP value of 3.5 [42]. The minimum value of the heating capacity is 5kW [43] where the maximum heating capacity is set at 10kW.

4.2.1.4 *Renewable energy source*

To meet the energy demand and the operational cost, PV panels are placed. The size of the PV panels is, in this case, the variable with a minimum of 5 m^2 and a maximum size of 30 m^2. The maximum size of PV system is limited based on available roof area on south façade. The efficiency of the PV panel is 0,12 % and has an emissivity and absorptance of 0,9. These values are based on the type 562a in TRNSYS.

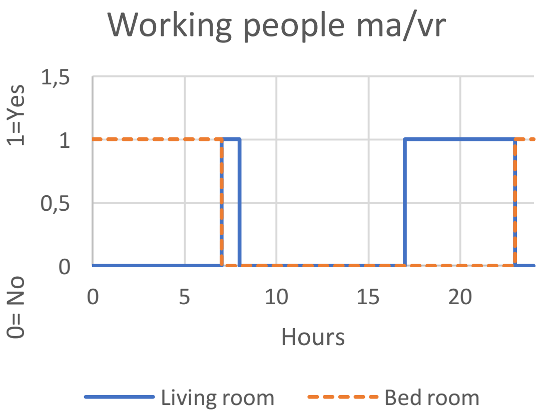
Table 4.2 Overview of all design parameter and value range

Design parameters	Min	Max	Steps	Unit	Reference
Rc-value	6	10	3	m^2K/w	[38], [39]
U-value	1,43	0,52	3	m^2K/w	[44]
Infiltration	0,12	0,60	3	ACH [1/h]	[45], [10]
WWR	20	60	3	%	[10]
Orientation	North-South	South-North	2		
PV system	5	30	3	m2	-
Heat pump C	5	10	3	kW	-
TOTAL Variants			**1458**		

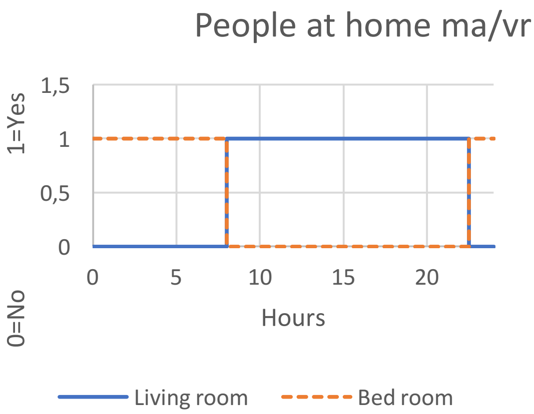
4.2.2 Operational scenarios

4.2.2.1 *Occupants profile*

Two occupancy profiles, that represents working people and retired people as shown in Figure 4.1, are used in the case study. One profile where all persons are leaving during the day and one profile where all persons remain in the house. These profiles are divided as well into the floor levels, respectively living room/ kitchen and bedroom. The profiles regulate the heating set point in the building, based on and the Dutch ministry [10], [46] and the internal heating gain. [45]. Based on the occupants profile several peak internal gains are set what results in the average internal heating gains as shown in Figure 4.2ab.



(a)



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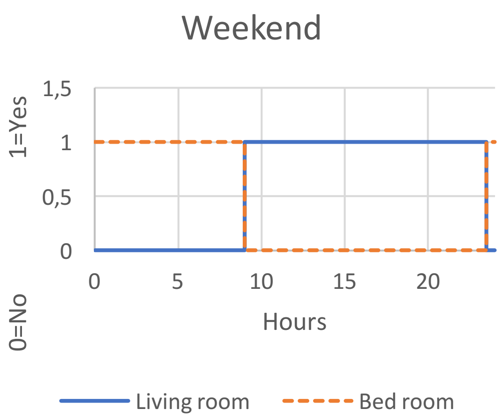
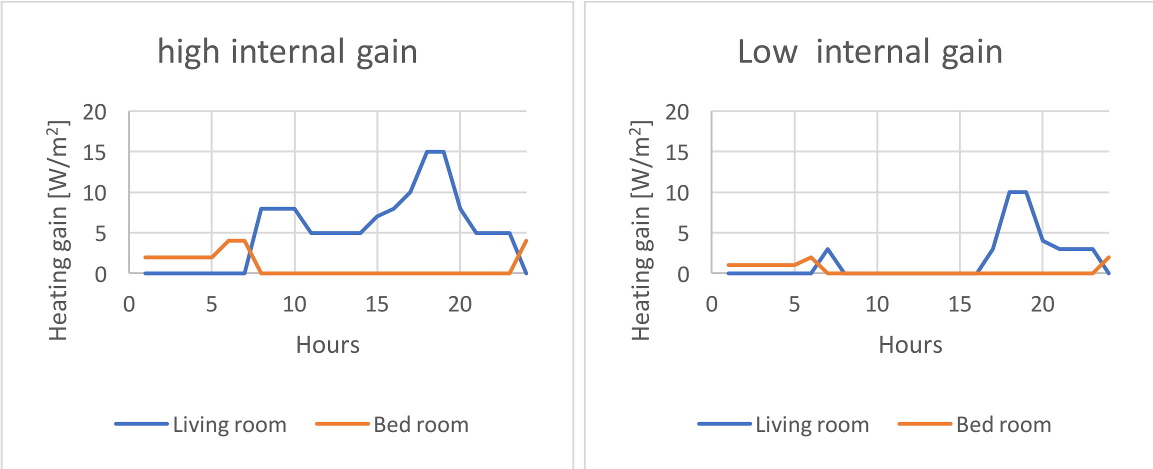


(c)

Figure 4.1 The occupant profile of: a; working people. b; people who stay at home c; weekend



(a) (b)

Figure 4.2 Internal heating gains profile for the different scenarios with an average of: a; 6 W/m^2. b; 2 W/m^2

4.2.2.2 *Ventilation*

Building is ventilated using natural ventilation and mechanical ventilation to provide fresh air and to reduce summer overheating. Natural ventilation occurs through the windows of the building when the indoor temperature is between 22°C and the 26°C. in all other cases, the ventilation is regulated by using mechanical ventilation. A minimum ventilation rate of 0,9 dm^3/s per m^2 has to be maintained in Dutch houses [47]. For the different scenarios, the maximum ventilation rate is set to 1,5 dm^3/s per m^2 as defined in [Hoes, 2014] [45].

In the building, a ventilation heat recovery system is installed to reduce the heating energy demand. The heat recovery is set to an efficiency of 95%. The bypass of the heat recovery system is based on [Hoes, 2014] and described below [45]:

$T_{room} > T_{Heating\ setpoint}$

$T_{ambien\ t} > T_{room}$

$T_{ambien\ t} > 10°C$

4.2.2.3 *Shading*

In the reference building, only manual shading is used on the south façade. In this research, shading is used on all windows and are controlled based on indoor temperature and solar radiation on windows, to lower the overheating hours. The minimum and maximum radiation are defined in [Hoes, 2014] and [Kotireddy, 2015] and are respectively 250 W/m^2 and 350 W/m^2 for lowering the shadings, and 200 W/m^2 and 300 W/m^2 for raising the shadings [45], [10].

Table 4.3 Overview of all operational scenarios and value range

Scenario	Min	Max	Steps	Unit	Reference
Number of occupants	2	6	2	persons	-
Internal heat gains	2	6	2	W/m2	[45]
Occupants	Evening	All day	2		-
Ventilation	0,9	1,5	2	ACH	[45]
Shading ON	250	350	2	W/m2	[45], [10]
Shading OFF	200	300	2	W/m2	[45], [10]
Heating setpoint (occ)	18	23	2	°C	[10], [46]
Heating setpoint (unocc)	14	18	2	°C	[10], [46]
TOTAL Scenario			**32**		

4.2.3 Performance indicators

4.2.3.1 *Heating demand, peak load and Energy total electricity demand*

The heating demand and peak load are obtained from the heat pump in TRNSYS. The net energy electrical consumption will be defined by all electrical consumptions from the heat pump, heat recovery system and all the pumps installed in the building minus the generated electricity from the PV panels. This can be expressed as followed:

$$P_{total} = \left(P_{heat\ pump} + P_{heat\ recovery} + P_{pumps}\right) - P_{PV} \qquad \text{Equation 4.1}$$

4.2.3.2 *Comfort*

The overheating hours are calculated based on a calculated minimum (lower) and maximum (upper) temperature as used in [Peeters et al, 2009] [48]. The upper and lower temperature are defined as followed:

Upper and lower band

$$T_{upper} = T_n + w\alpha$$

Equation 4.2

$$T_{lower} = T_n - w(1 - \alpha)$$

Equation 4.3

where w and α defining the parametric values as function for the PPD. For this project a 10% PPD has been chosen:

Table 4.4 Parameter values as function of PPD [48]

	10% PPD	20%PPD
w	5°C	7°C
α	0,7	0,7

And:
T_n= Neutral temperature
For bedroom:

$T_n = 16°C$	for	$T_{e,ref} < 0°C$	Equation 4.4
$T_n = 0{,}23T_{e,ref} + 16°C$	for	$0°C \leq T_{e,ref} < 12{,}6°C$	Equation 4.5
$T_n = 0{,}77T_{e,ref} + 9{,}18°C$	for	$12{,}6°C \leq T_{e,ref} < 21{,}8°C$	Equation 4.6
$T_n = 26°C$	for	$T_{e,ref} \geq 21{,}8°C$	Equation 4.7

For living room:

$T_n = 0{,}06T_{e,ref} + 20{,}4°C$	for	$T_{e,ref} < 12{,}5°C$	Equation 4.8
$T_n = 0{,}36T_{e,ref} + 16{,}63°C$	for	$T_{e,ref} \geq 12{,}5°C$	Equation 4.9

The reference temperature has been defined by the following formula:

$$T_{e,ref} = \frac{(T_{Today} + 0{,}8T_{Today-1} + 0{,}4T_{Today-2} + 0{,}2T_{Today-3})}{2{,}4} \quad \text{Equation 4.10}$$

T_{Today} = average temperature of min and max of that day
$T_{Today-n}$ = day's past of today

this results in:

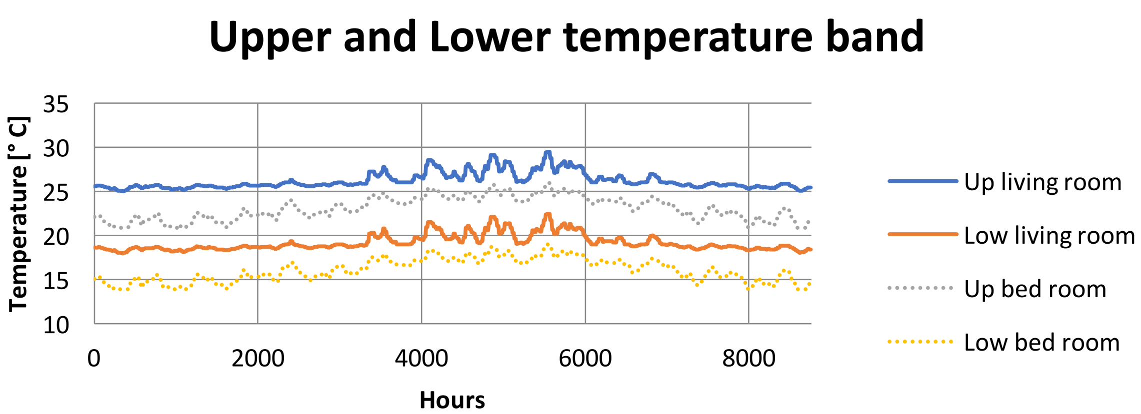


Figure 4.3 Upper and Lower temperature band for determining over and under heating hours

4.2.3.3 Costs

The operational cost and total cost of ownership are calculated to assess the running costs and investment costs of a building design. The operational cost is calculated as followed:

$$Operational\ cost = (energy\ consumption - energy\ generated) * Energy\ price \quad \text{Equation 4.11}$$

where:

$$Energy\ consumption(EC) = EC_{light} + EC_{heatpump} + EC_{pumps} + EC_{...} + \cdots \quad \text{Equation 4.12}$$

$$Energy\ generated = EG_{PV}$$ Equation 4.13

$$Energy\ price = energy\ tax + cost\ renewable\ energy\ storage\ + cost\ power\ + cost\ distributor$$ Equation 4.14

The energy price is set to € 0,18863 /kWh according to the energy cost of the year 2016 in the Netherlands [49].

The total cost of ownership is calculated based on investment cost of different design variants shown in Table 4.5-4.7 and the operational cost. [8] [15] [16].

Table 4.5 Insulation costs based on the thickness of the insulation

RC_roof	€/m²	Total	RC_wall	€/m²	Total	Grand total
7	20,73	**850,75**	6	17,17	**3632,15**	**4482,90**
8,5	25,43	**1043,50**	7,5	21,86	**4625,85**	**5669,35**
11	33,20	**1362,53**	10	29,64	**6270,60**	**7633,13**

Table 4.6 Window type cost

Type	cost [€/m²]	U-value	Average u value
HR+	75	1,3-1,6	1,45
HR++	80	1,2	1,2
HR+++	120	0,5-0,9	0,7

Table 4.7 Cost of PV panels based on average costs.

m²	Average **cost [€/m²]**	**Total cost**
5	149,63	748,15
12,5	149,63	1570,38
30	149,63	4488,9

Table 4.8 The different performance indicators used in this project

Performance indicators		Unit
Heating demand		kWh
Peak Load		kW
Net energy electrical consumption		kWh
Overheating hours		H
Under heating hours		H
Operational costs		€
Total Cost Ownership		€

4.3 Predicted performance compared with BENG in literature.

The used case-study building is based on [37] and simulated in TRNSYS. In 'variant calculations for requirements of net zero energy buildings' the energy consumption of several building variants are calculated based on NEN7120 [36]. Figure 4.4 shows the energy consumption of the different BENG types as used in [36]. In orange, the calculated energy consumption of the case-study building is given. As can be seen, the energy consumption of the case-study building is around 21 kWh/m^2 a year.

All given values in BENG are above the case-study results, however, the values calculated with the NEN 7120 are monthly average values where the TRNSYS model calculates a dynamic hourly average. Therefore, model accuracy is not evaluated. However, looking to Figure 4.4 the results of the TRNSYS model are close to the calculated BENG types. Aside from the difference between the transient calculation of the BENG models and the dynamic calculation of TRNSYS, some assumptions have been made in the TRNSYS model, for instance occupants behaviour, Window type and installations. These assumptions have influence on the energy consumption of the building. However, comparing the data with the BENG types, the TRNSYS model don't show substantial anomalies.

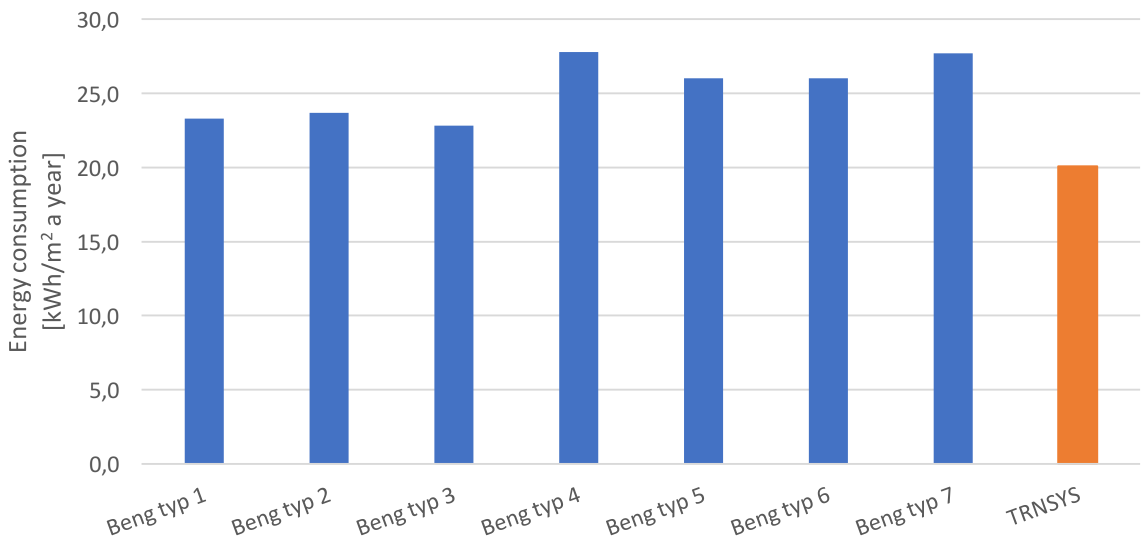


Figure 4.4 Monthly energy consumption of the reference building compared with the TRNSYS simulation model of the case-study building.

5 Case study results: analysing and visualizing sensitivities and interactions

In this chapter, the simulation results are shown. At first, the results of the most influential parameters over different performance indicators are shown. Second, the interaction between different parameters is shown. Third, a comparison between different performance indicators is shown and at last the visualisation tool for the stakeholder is explained.

5.1 Identifying of the most influential parameters

To identify the most influential parameters over the different performance indicators, two methods are used. At first, the boxplot method is used. In this method, the effect of design parameters and operational scenarios on performance indicators are visualised separately. Based on the outcome of the boxplots the most influential parameters can be distinguished. The second method is the variance-based sensitivity analysis method. These results will be visualised in bar plots and finally compared with the boxplots of method one.

5.1.1 Method 1: Boxplots

Figure 5.1-Figure 5.3 shows the variation of heating demand, overheating hours and the total cost of ownership for different design variants across considered scenarios. Variation of these performance indicators with respect to scenarios are shown in Figure 5.4-Figure 5.6. The results for all scenarios are presented in Appendix D. The size of the boxplot shows the numerical data based on their quartiles. The higher the difference between the boxplots of one parameter, indicates a higher influence of that specific parameter. It can be observed from Figure 5.1 and Figure 5.2, that the boxplot shows an enormous difference between the three values of the infiltration with respect to the other parameters and is indicated in orange in both figures. This indicates that the infiltration has a high influence on the heating demand and over-heating hours, and is, therefore, the most influential parameter for both performance indicators.

Figure 5.3 shows the boxplots of the different parameters of the total cost of ownership. In contrast to heating demand and overheating hours, PV panel size, thermal resistance and window-to-wall ratio, indicated in orange in Figure 5.3, have high influences on the total cost of ownership. Similarly, by comparing variation of these performance indicators for considered scenarios in Figures 5.4-5.6, it can be observed that the heating set-point is the most influential on all performance indicators However, this method does not quantify the influence of design parameters and scenarios on performance indicators. Hence, variance-based sensitivity analysis is used to quantify the influence and these results are described in next section.

Influence of design parameters

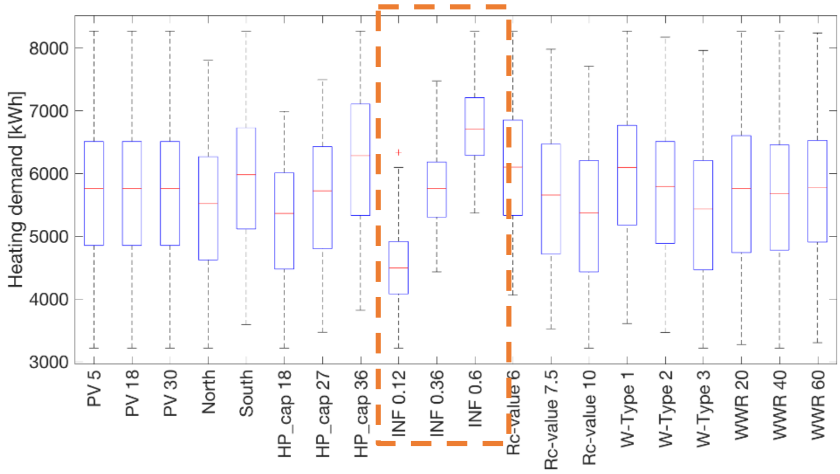


Figure 5.1 Boxplot of the heating demand and design parameters where the infiltration shows the most influence on the heating demand

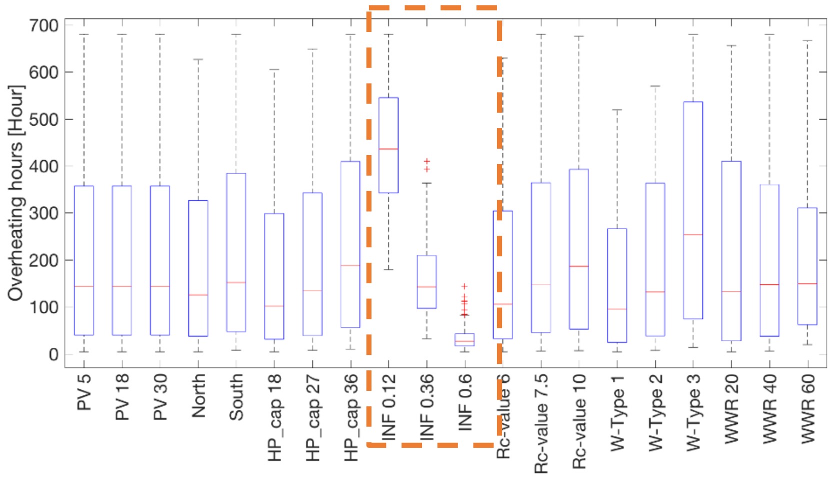


Figure 5.2 Boxplot of the overheating hours and design parameters where the infiltration shows the most influence on the overheating hours

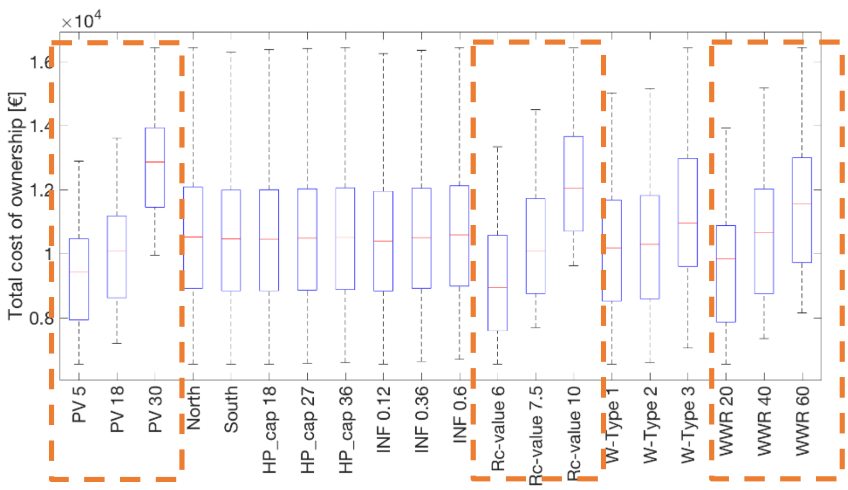


Figure 5.3 Boxplot of the total cost of ownership and design parameters where the PV panel size, thermal resistance and window-to-wall ratio shows the most influences on the total cost of ownership

Influence of operational scenarios

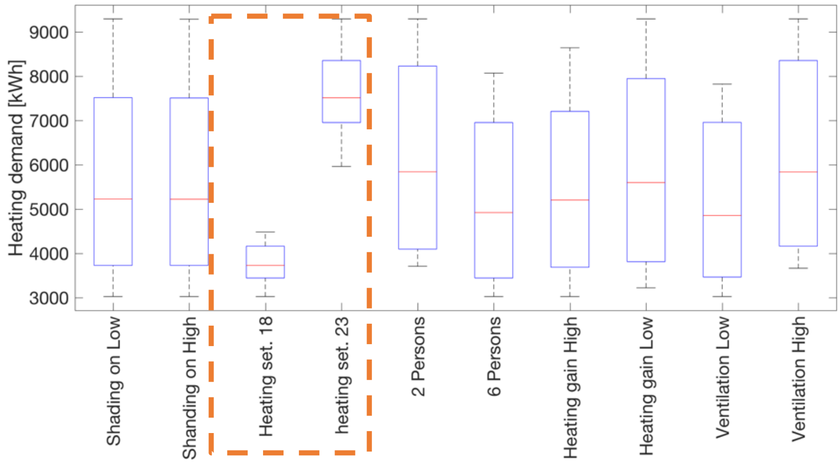


Figure 5.4 Boxplot of the heating demand and operational scenarios where the heating set-point shows the most influences on the heating demand

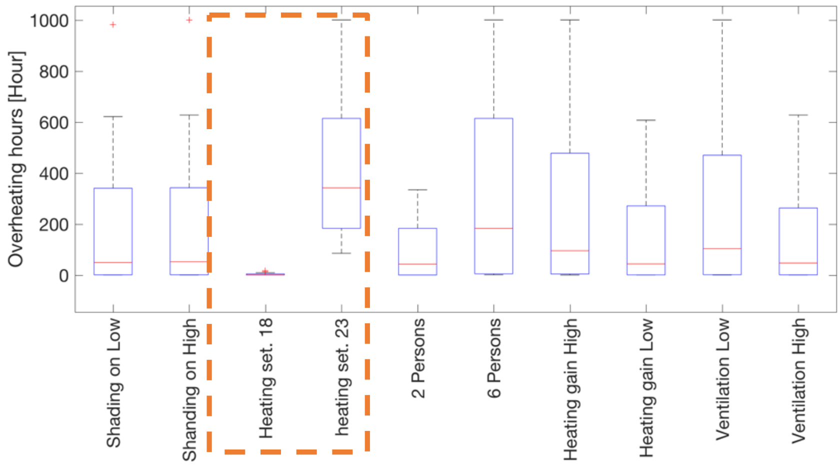


Figure 5.5 Boxplot of the overheating hours and operational scenarios where the heating set-point shows the most influences on the overheating hours

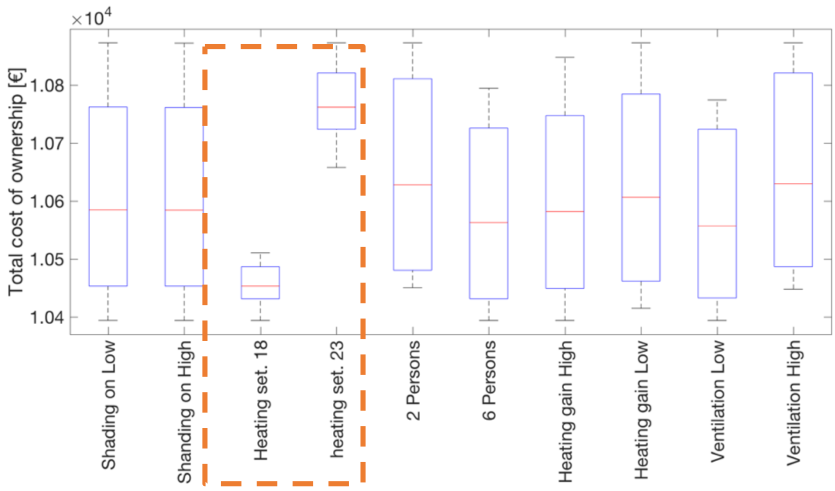


Figure 5.6 Boxplot of the total cost of ownership and operational scenarios where the heating set-point shows the most influences on the total cost of ownership

5.1.2 Method 2: Variance-based sensitivity analysis

The variance-based sensitivity analysis has been used to quantify the most influential parameters of each performance indicator. For this sensitivity analysis, $S_{k,\ldots} = \frac{V_{k,\ldots}}{V(Y)}$

Equation 2.8 have been used from Sobol's method. A schematic overview of this method can be found in Figure 3.4. In this method, the percentage is taken over all the variances of each parameter resulting in an influence rate between 0 and 1.

Figure 5.7 shows the results of variance-based sensitivity analysis of the design parameters and the operational scenarios on the heating demand, overheating hours and the total cost of ownership. Figure 5.7 shows, as observed in Figure 5.1-Figure 5.6, that the infiltration rate is the most influential design parameter on the heating demand and overheating hours. Where the PV panel size, thermal resistance and window-to-wall ratio are the most influential design parameter of the total cost of ownership, as can be seen in Figure 5.7e. Similarly for operational scenarios, the most influential parameter is in all cases is the heating set-point as shown in Figure 5.7b, 5.7d and 5.7f. In addition for the heating demand and total cost of ownership, the heating set-point has high influence with respect to all the other operational scenarios. For overheating hours, number of occupants and their corresponding activity have relatively high influence.

As described in section 3.2 the design parameters and operational scenarios are investigated separately. For this, the mean value is taken over the design parameters when investigating the most influential parameter for the operational scenarios what results in a most influential operational scenario over a generalised building design. To investigate the most influential operational scenario with respect to different building designs, the variance-based sensitivity analysis method can be used as well as can be seen in Figure 5.8. Figure 5.8 shows the most influential operational scenario of the heating demand of two different building designs. As can be seen, the heating set-point is in both cases, as well as the generalised building design, the heating set-point. The interaction between different parameters, design parameters or operational scenarios or between both, are described in the next section.

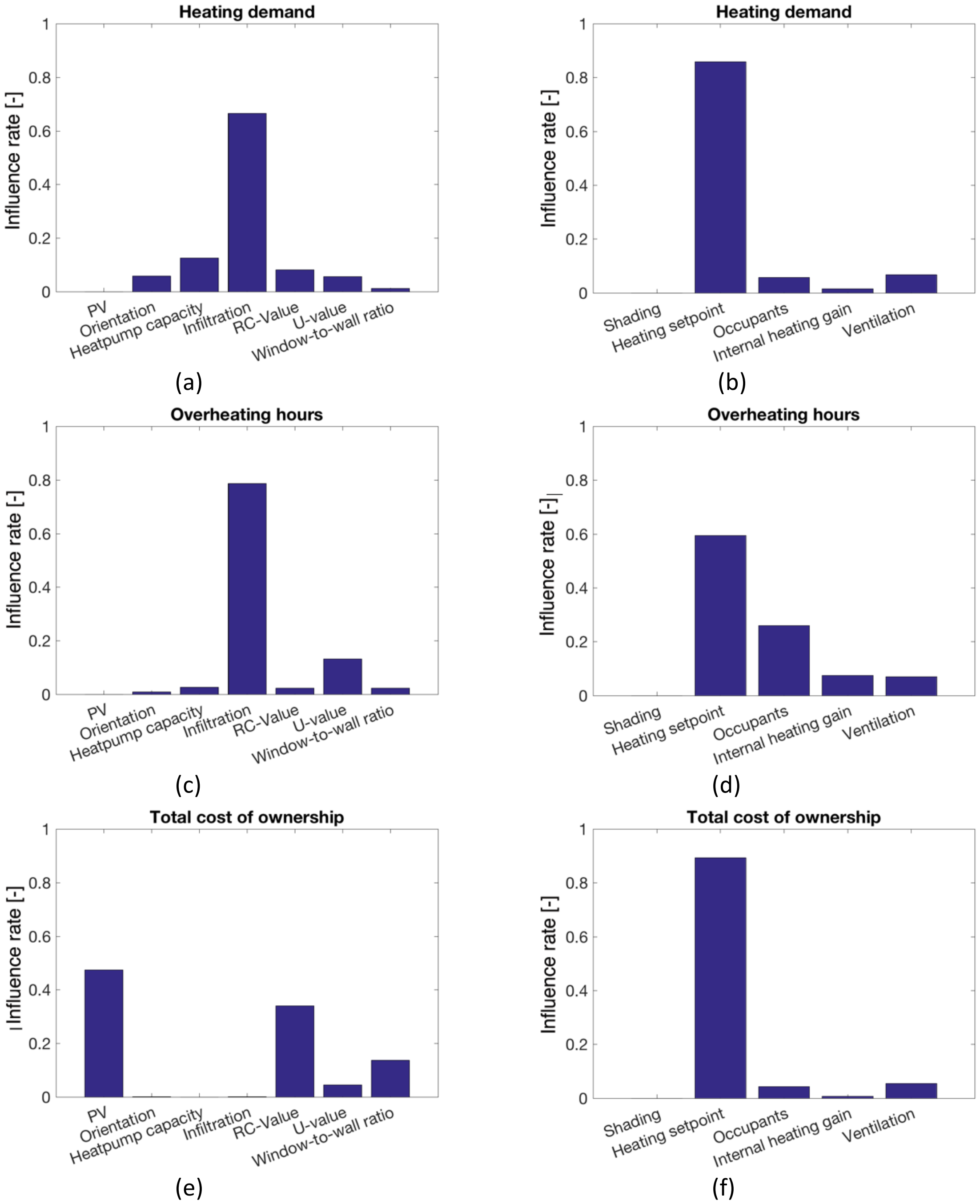
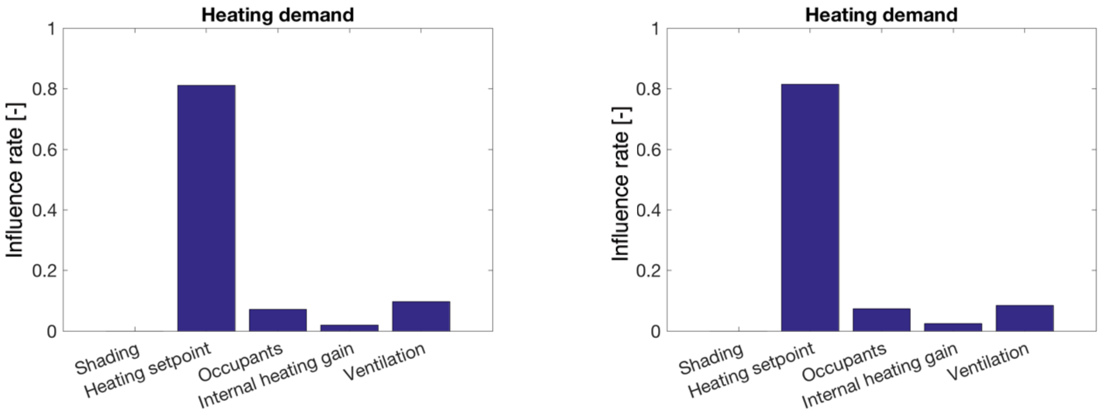


Figure 5.7 Most influential parameter calculated with the variance based sensitivity analysis. With the left column, the most influential parameters of the design parameters and at the, right the most influential parameters of the operational scenarios.



(a) (b)

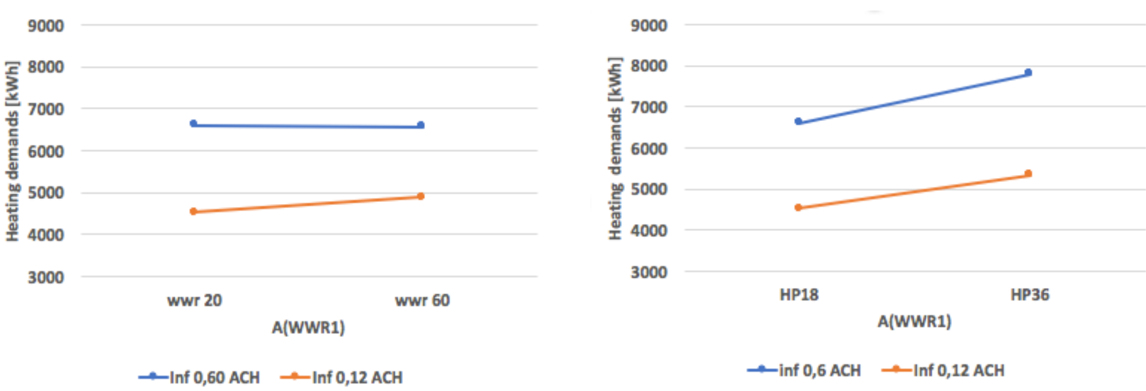
Figure 5.8 Most influential parameter calculated with the variance based sensitivity analysis. With a building design x and b building design y

5.2 The interaction between different parameters

For design support of zero energy buildings, not only the most influential parameter is of interest, but as well the interaction between the different parameters. This section describes the results of these interactions between the different parameters for the design parameters and operational scenarios.

5.2.1 Method 1.1: Local sensitivity analysis for finding the interactions between parameters

The local sensitivity analysis as explained in [O'Brien et al, 2011] has been used to identify the interactions between different parameters as first method. In this method, the deviation between the minimum and maximum values over two different parameters have been investigated. The deviation between the created lines (between the minimum and maximum), indicates the interactions. Figure 5.9ab shows respectively the local sensitivity analysis between the infiltration and the window-to-wall ratio, and the interaction between the infiltration and the heat pump capacity. As can be seen, the interaction is not great in both figures, however, the differences between the lines of the investigated parameters can be expressed in a percentage what results in Table 5.1. based on these percentages we can see that the local sensitivity analysis shows that the window-to-wall ratio, heat pump capacity and the thermal resistance has an interaction with the infiltration.



(a) (b)

Figure 5.9 Comparison of the interaction between two parameters based on the local sensitivity analysis between a:window-to-wall ratio and infiltration and b: heat pump capacity and the infiltration

Table 5.1 Interaction between infiltration and other parameters based on local sensitivity analysis

Interaction	Percentage [%]
Infiltration – Window-to-wall ratio	20
Infiltration – Heat pump capacity	18
Infiltration – Thermal resistance window	3
Infiltration – Thermal resistance wall	15
Infiltration – Orientation	3
Infiltration – shadow	0

5.2.2 Method 1.2: variance-based sensitivity analysis for finding the interactions between parameters

To identify the interactions the pooled variance over a parameter is taken, followed by calculating the variance over the pooled variance between the input values of the different parameters. A schematic overview can be found in Figure 3.5.

Figure 5.10a-b shows the interactions between the infiltration and all other parameters of heating demand and overheating hours. As can be seen in Figure 5.10a, the infiltration has a strong interaction with the window-to-wall ratio, the heat pump capacity and the thermal resistance where Figure 5.10b shows that the infiltration has a strong interaction with the window types. Similarly, for operational scenarios, as can be seen in the figure, the most influence between the heating set-point and the other parameters can be found between the heating set-point and the number of occupants. Also, there can be seen that the heating set-point has some interaction with the ventilation and the internal heating gain, but not with the shading. Figure 5.10c shows the interaction between the heating set-point and all other parameters on the heating demand. Here, the ventilation and the heating set-point has the strongest influence between each other. Although, the difference of the interaction of the other parameters and the heating set-point is lower than the interaction between the heating set-point and the other parameters in Figure 5.10d. The interaction between one parameter and all other parameters of the different performance indicators can be found in Appendix F.

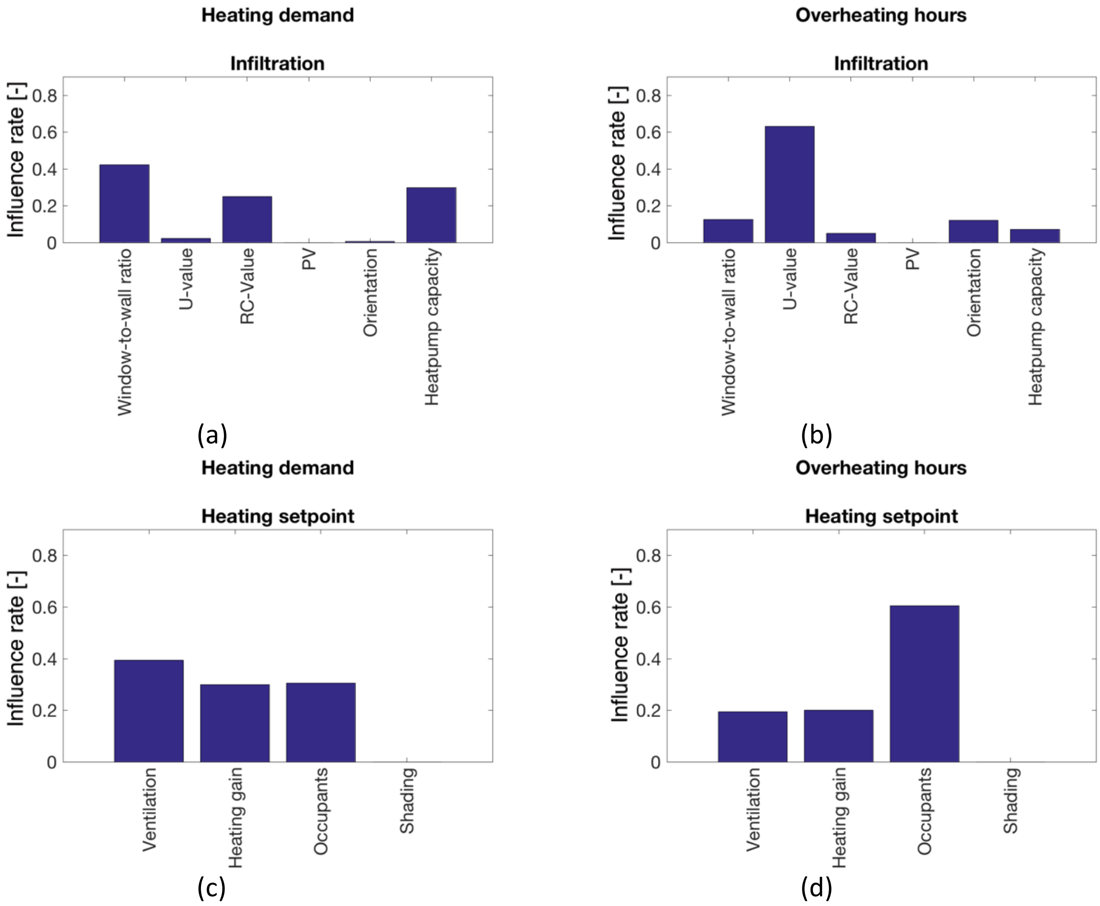


Figure 5.10 Interaction between the infiltration (a, b) and all other parameters and the heating set-point (c, d) and all other parameters calculated with the variance based sensitivity analysis

The influence rate between the infiltration and the RC-value in Figure 5.11a shows a value around 0.3 where the influence rate between the RC-value and the infiltration in Figure 5.11b shows an influence rate of 0.6. Although the interactions between these two parameters are the same, the values are different. Based on these two graphs we can see that the interaction between the infiltration and the window-to-wall ratio and the infiltration and heat pump capacity is higher than all the interactions of the RC-value and all other parameters.

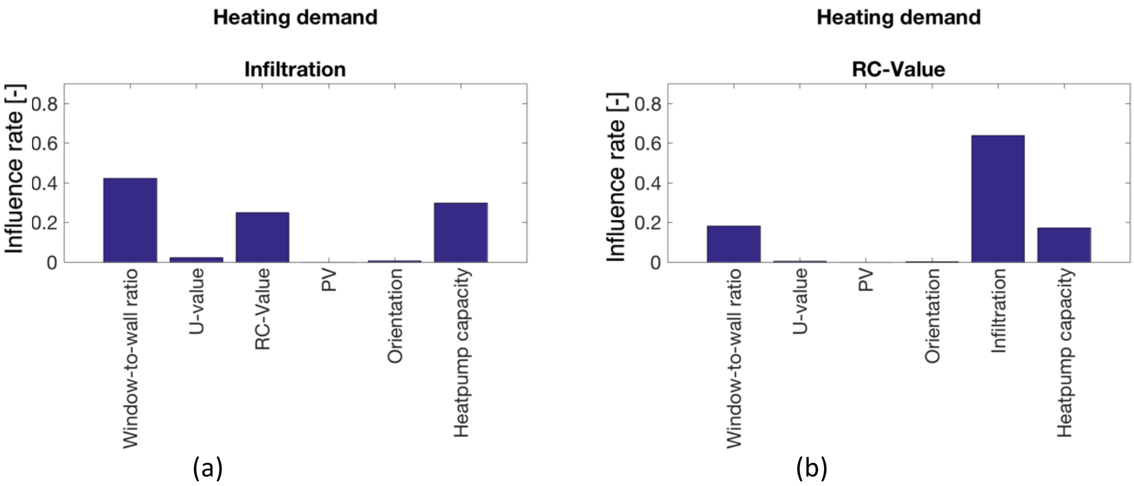


Figure 5.11 Interaction between two parameters with a, the infiltration and all other and b, the interaction between the RC-value.

5.2.3 Method 2.1: 3D-scatterplot for finding the most influential combination between parameters

To give a more insight of the interaction between two parameters, the most influential combination between these parameters can be defined. At first, a 3D-scatterplot is visualised where all values are set out to two parameters. Figure 5.12 shows the 3D-scatterplot where all values of the average design parameters are set out to the infiltration and the window-to-wall ratio of the heating demand. As can be seen, when the window-to-wall ratio and the infiltration increase the heating demand increases. Comparing the lowest window-to-wall ratio with the highest window-to-wall ratio for an infiltration of 0.6ACH shows, that for a high window-to-wall ratio deviation of all the values of the heating demand is higher than for the low window-to-wall ratio. However, when we take the variance of the values we can see that the variation is higher for a low window-to-wall ratio compared with the high window-to-wall ratio as can be seen in Figure 5.13. based on Figure 5.13 we can see that the influence on the heating demand is high for a high window-to-wall ratio in combination with a high infiltration.

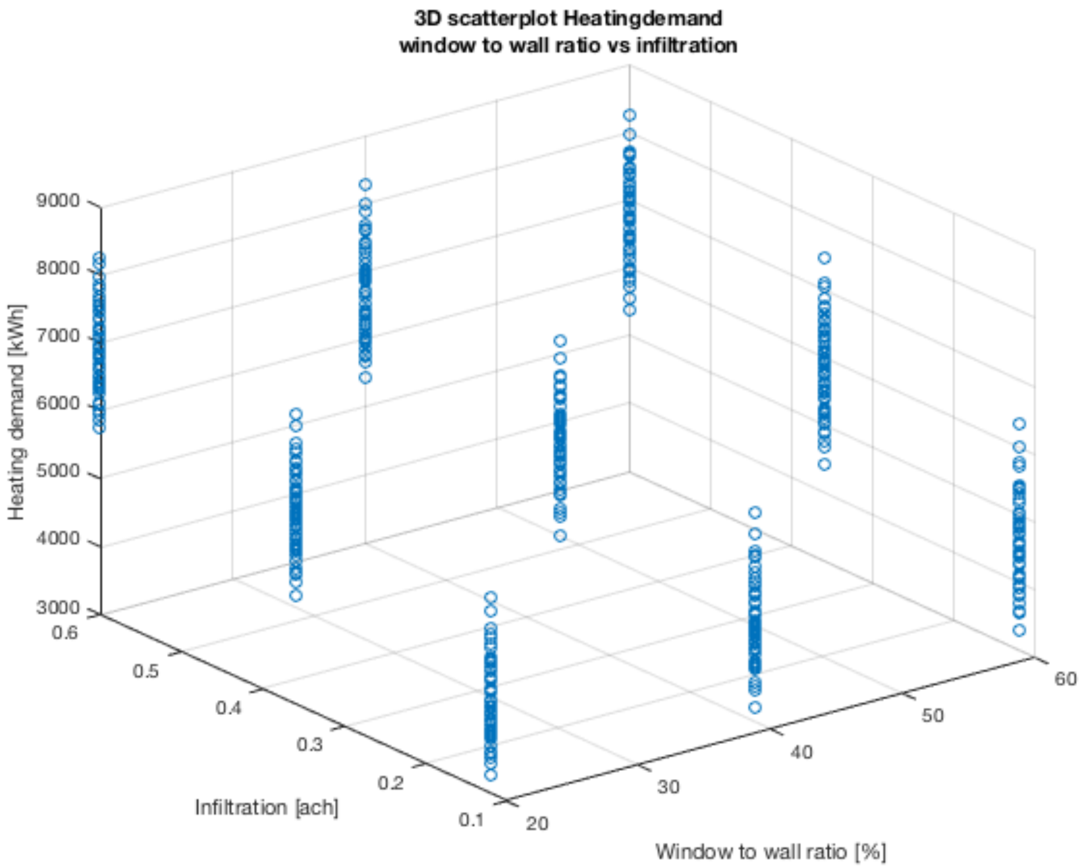


Figure 5.12 3D scatterplot of the heating demand variation with the infiltration and window-to-wall ratio

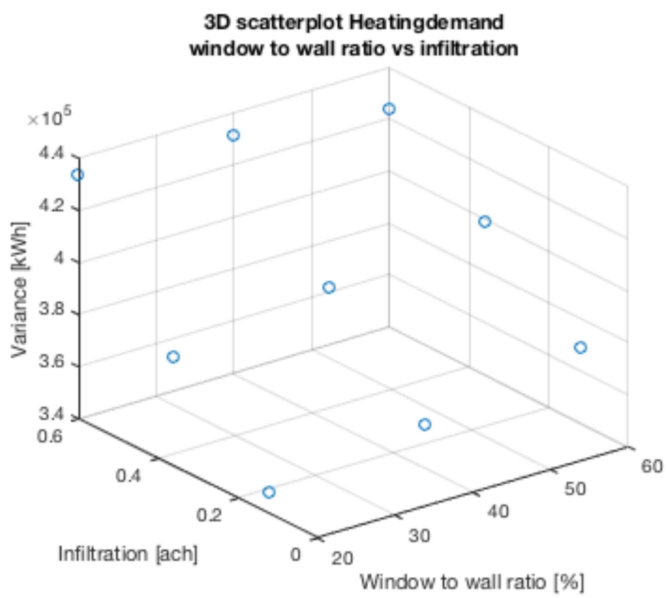


Figure 5.13 Variance of Figure 5.12

5.2.4 Method 2.2: Variance-based sensitivity analysis for finding the most influential combination between parameters

Figure 5.14a-c shows the most influential combination between two design parameters for the heating demand. Figure 5.14a shows, that the influence between the infiltration and window-to-wall ratio increases when the window-to-wall ratio increases. Also, can be seen that the impact of the window-to-wall ratio on the interaction is greater than the impact of the infiltration. It can also be observed that the interaction between the two parameters reduces when the window-to-wall ratio increases. Figure 5.14c shows that the influence between the heat pump capacity and the infiltration decreases when the infiltration increases, where the influence increases when the heat pump capacity increases.

Figure 5.14b and Figure 5.14d shows the most influential combination between the heating set-point, and respectively the internal heating gain and the number of occupants in the building for overheating hours. Figure 5.14b shows that there is no interaction between the low heating set-point and internal heating gains. When the heating set-point is set to high values, there is an interaction with the internal heating gain. As can be seen in Figure 5.14b, the interaction between the two operational scenarios decreases for the high heating set-point, when the internal heating gain is higher. Figure 5.14d also shows as well that the low heating set-point and in this figure number of occupants results in no. However, the number of occupants in the building and the low heating set-point shows that the influence rises when the number of occupants in the building increases.

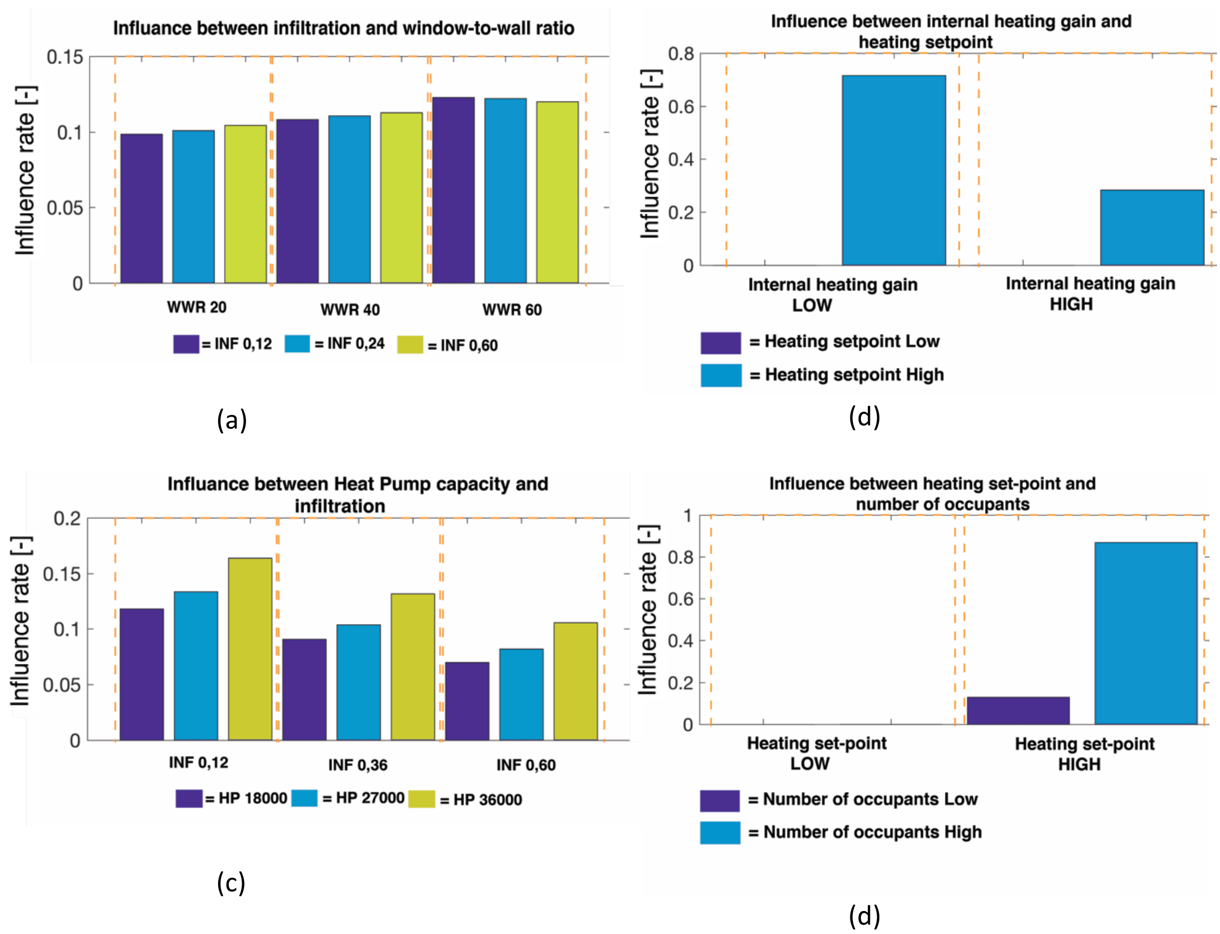


Figure 5.14 Most influential combination between different parameters, calculated as shown in Figure 3.6

5.3 Combining most influential parameter with the interaction between parameters

5.3.1 Method: parallel coordinate plot

Figure 5.15 show the parallel coordinate plots of heating demand, total cost of ownership and overheating hours. All other results are shown in appendix G. As explained in section 3.3, the parallel coordinate plots show the most influential parameter of a specific performance indicator.

Figure 5.15a shows the impact on the most influential parameter on the heating demand when the infiltration and the heat pump capacity changes. Line colour indicates the infiltration and the line type indicates the heat pump capacity. When the infiltration is increasing from 0.12 ACH to 0.6 ACH, the influence of infiltration rate reduces, whereas the influence of heat pump capacity increases. When the heat pump capacity increases in value we can see that the infiltration decreases as most influential parameter whereas the influence of the heat pump increases as well.
Figure 5.15b shows the impact on the most influential parameter of the heating demand when the infiltration and the window-to-wall ratio changes. Also here, the line colour indicates the infiltration, but the line type indicates now the window-to-wall ratio. The influence of increasing values of the

infiltration in Figure 5.15b is the same as in Figure 5.15a. The effect of an increasing window-to-wall ratio for a low infiltration value is high, but this effect is decreasing when the infiltration is increasing.

Figure 5.15c shows the impact on the most influential parameters of the thermal resistance, indicated in the line colours, and the window-to-wall ratio, indicated in the line types, for the total cost of ownership. As can be seen in this figure, when the Rc-value is increasing, the influence of the thermal resistance is decreasing. The PV panel size as most influence parameter, however, will be increased. The effect of the window-to-wall ratio in combination with the thermal resistance shows that the effect of a 20% window-to-wall ratio to a 40% window-to-wall ratio has less influence than the step from 40% to 60% window-to-wall ratio, as can be seen clearly in Figure 5.15c at the Rc-value parameter.

Figure 5.15d and Figure 5.15e shows both the parallel coordinate plots of the overheating hours. Figure 5.15d shows the parallel coordinate plot where the effect on the most influential parameter is investigated of the heating set-point and the number of occupants, where Figure 5.15e shows the interaction based on the heating set-point and the internal heating gain. In both figures, the heating set-point is defined by the line colour where the other parameters are defined by the line type. As can be seen in Figure 5.15e, a low heating set-point results in a high influence on the overheating hours. Increasing this parameter, the number of occupants will be the most influential parameter. When the internal heating gain is increasing when the heating set-point is low, the heating set-point will decrease as the most influential parameter, where the number of occupants will be more important. Considering the increase of the internal heating gain for a high heating set-point, we can see that the number of occupants will be decreasing where the internal heating gain will increase as the most influential parameter.
Looking to Figure 5.15e the difference in the heating set-point is equal to Figure 5.15d. However, by investigating the number of occupants in combination with the heating set-point shows, for a low heating set-point, that the heating set-point is decreasing as the most influential parameter, where the number of occupants is increasing. Considering a high heating set-point in combination with a high number of occupancy results in, according to this graph, the most influential parameter by the internal heating gain and the ventilation.

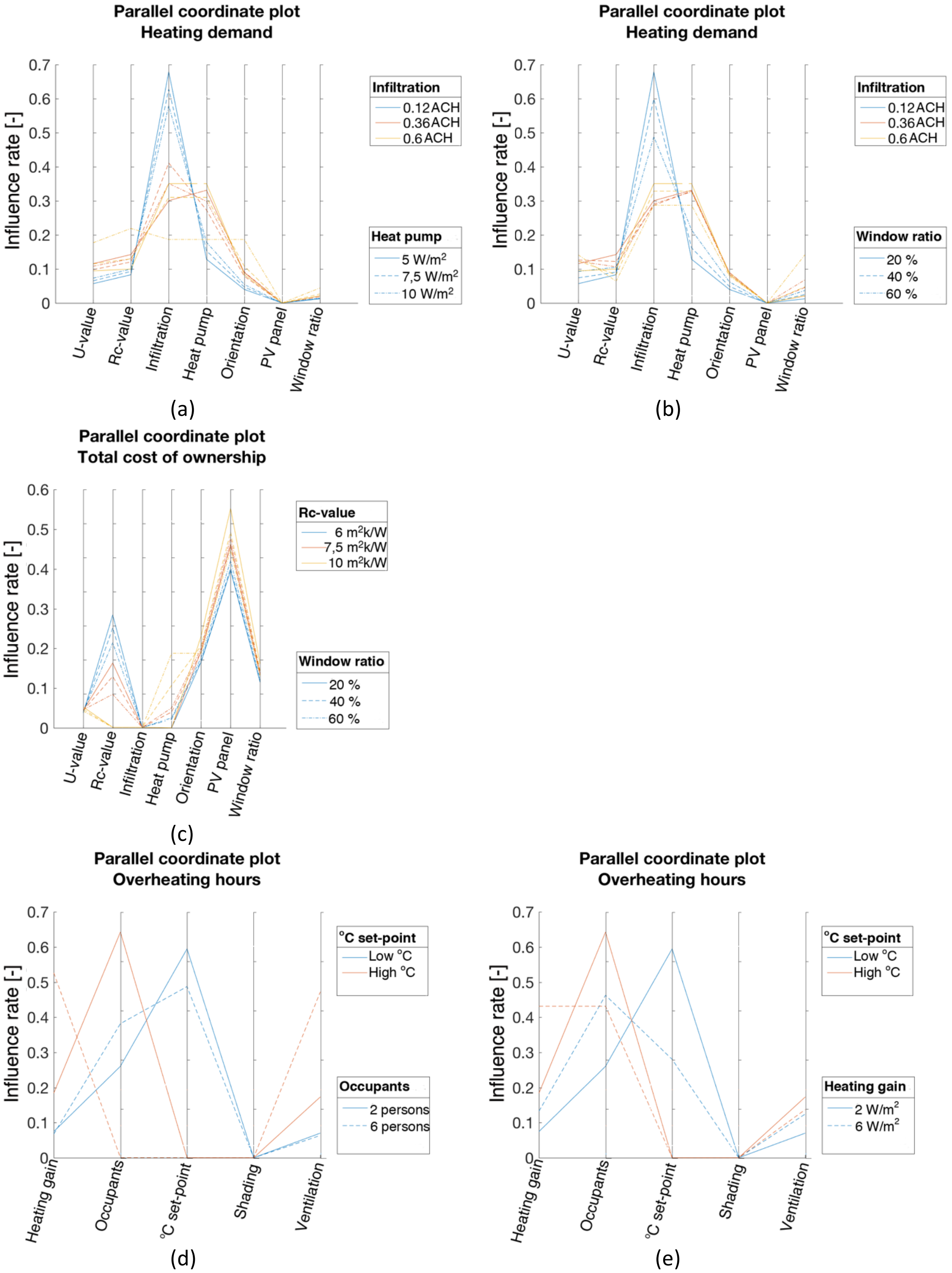


Figure 5.15 Parallel coordinate plots based on Figure 3.7 to show the most influential parameters of different performance indicators and to show the variance on the most influential parameter when two parameters changes in value.

5.4 Relation between performance indicators

As can be seen in section 5.1 and 5.2 the most influential parameters, and the interaction between different parameters are not the same for each performance indicator. To inform stakeholders about the effect of these differences, a scatterplot has been used. Here two different performance indicators are plotted against each other based on one parameter. In this way, the influence of the chosen parameter can be shown on both performance indicators. Also, the direction of the influence can be identified with these scatterplots.

To show the relation between different performance indicators, the average values, as used in the previous calculations and visualisations, are taken. Figure 5.16 shows the scatterplot, with corresponding histograms, of the influence of infiltration on the heating demand and total cost of ownership. It can be observed that, for a low infiltration, the heating demand is low. Increasing the infiltration results in an increase in the heating demand. This can be clearly seen in the histogram corresponding to the scatter plot. The histogram of Figure 5.16 shows that low infiltration results in low heating demand, which is between 3000 kWh and 6500 kWh with the most values around the 4500 kWh where high infiltration have a heating demand of between 5000 kWh and 8500 kWh with the most values around the 6800 kWh. This indicates that the infiltration has influence, similar to observations made in Figure 5.7a and therefore, it is the most influential parameter of the heating demand. Also, it can be seen in Figure 5.16 that for the total cost of ownership the spread of the infiltration is random. Here the histogram shows that the most values are around €12000, -. This can be seen in Figure 5.7e where the infiltration has little to no influence.

Figure 5.17 shows the scatterplot of the heating demand and overheating hours based on the heating set-point. As it can be seen form Figure 5.17, for both performance indicators the low heating set-point results, in both cases, in low values. Also, it can be seen that, for the high heating set-point, variation of heating demand is inversely proportional to overheating hours. This effect is caused by the number of occupants in the building, ventilation and internal heating gains as can be seen in appendix H.

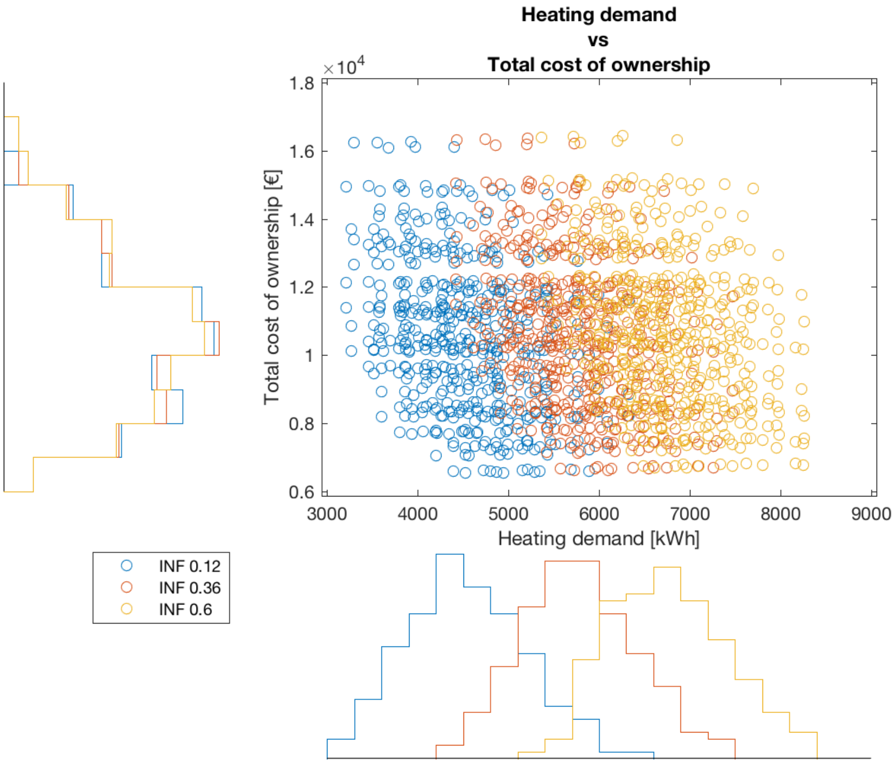


Figure 5.16 Scatterplot with corresponding histograms of the total cost of ownership and the heating demand where the infiltration is grouped.

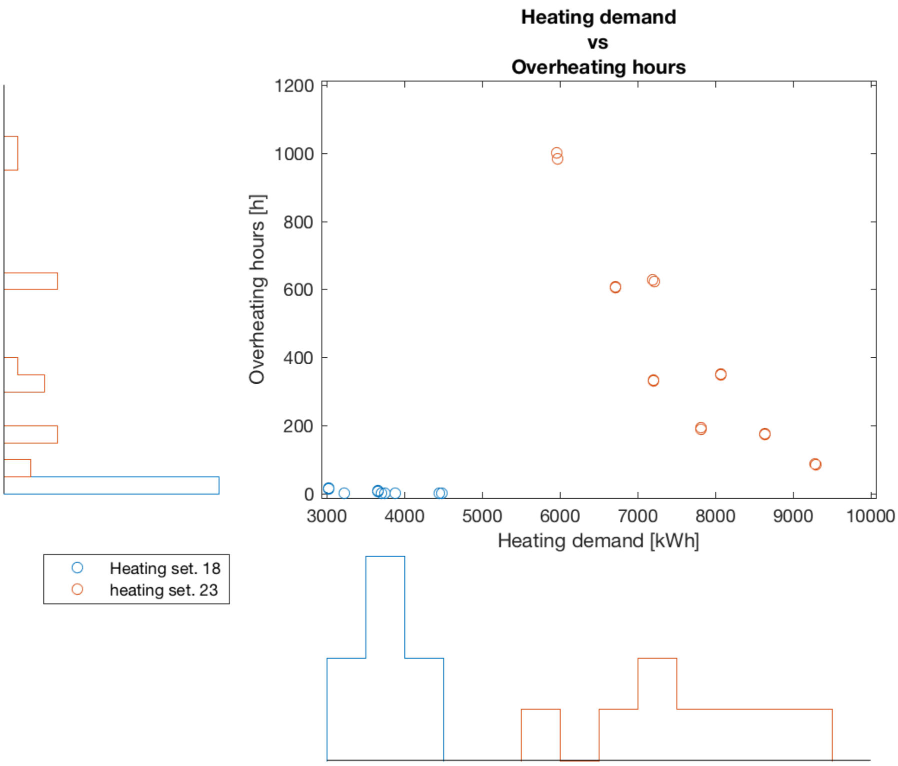


Figure 5.17 Scatterplot with corresponding histograms of the Overheating hours and the heating demand where the heating set-point is grouped.

5.5 Implementation of the visualisation methods for stakeholder in a proposed visualisation tool

To provide an interactive way of visualising the different results, a GUI is built in Matlab. The goal of the GUI is to provide all the information needed to inform a stakeholder over the most influential parameters, and to inform the stakeholder about the interaction between different parameters.
The GUI presented in this stage is divided in three parts and split in the visualisation tool by three tabs.

- Tab 1: Most influential parameter
- Tab 2: Interaction between different parameters & most influential combination of two parameters
- Tab 3: Relation between two performance indicators based one design parameter or operational scenario

A detailed description of the working of the visualisation tool can be found in appendix I.

5.5.1 Tab 1: Most influential parameter

The most influential parameter is visualised in the parallel coordinate plot as shown in Figure 5.15. Here, all parameters are set out to the influence rate [%] on a scale of 0-1 and divided in the design parameters or operational scenarios. Figure 5.18 shows an overview of the first tab. In this tab, the stakeholder can select a performance indicator and the design parameters or the operational scenarios. The influence of two design parameters or operational scenarios on the most influential parameter can be investigated by selecting these in the panel as shown in Figure 5.18. Here, the choice of input values can be selected to see the corresponding influence on the selected performance indicator. To distinguish the influence of the two parameters from each other, one parameter is defined by the line colour and the other-one by the line type as can be seen in Figure 5.18.

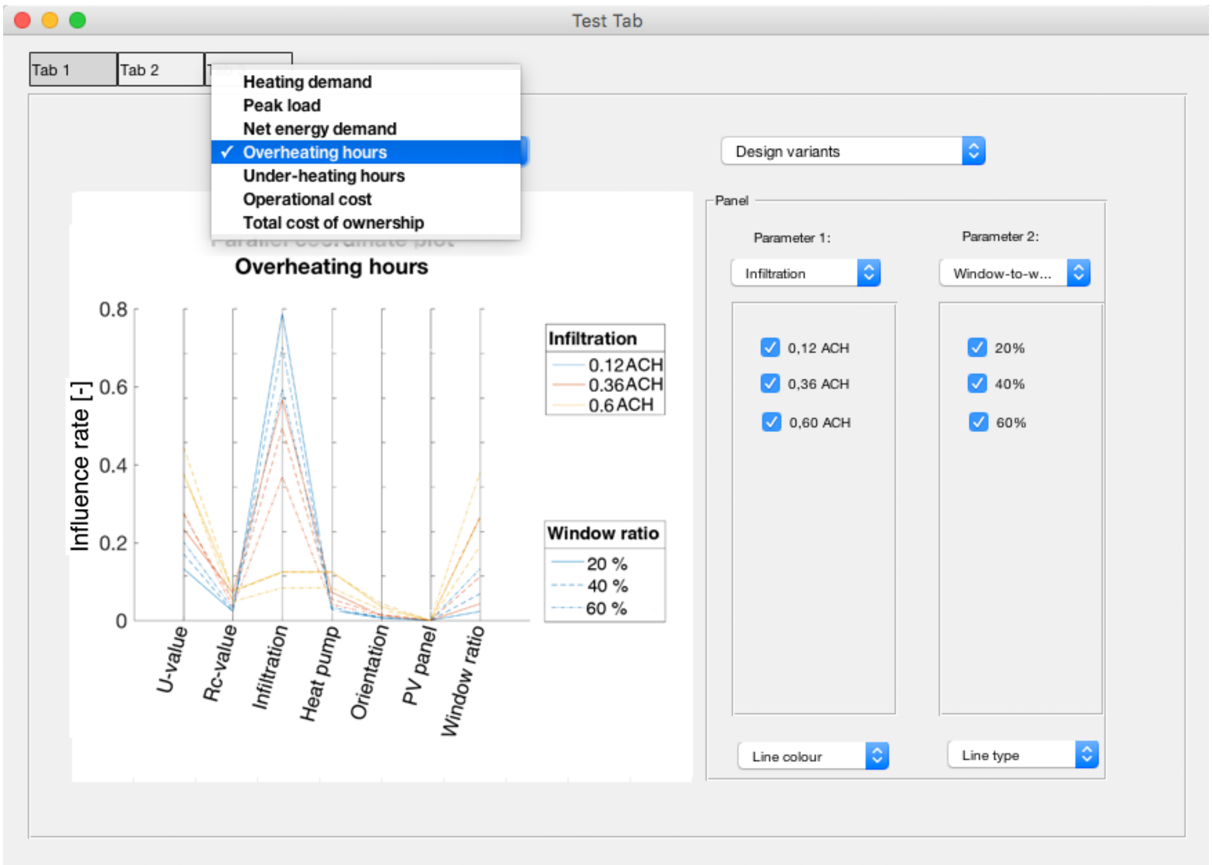


Figure 5.18 Total overview of tab 1 showing the parallel coordinate plot which shows the most influential parameter.

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5.5.2 Tab 2: Interaction between different parameters & most influential combination of two parameters

In the second tab the interaction between parameters and the most influential combination between parameters are shown in bar plots as can be seen in Figure 5.19. The interaction between parameters is shown in the upper part of the tool and are based on Figure 5.10, where the most influential combination is shown in the lower part of the tool and are based on Figure 5.14.
Also in this tab, first the performance indicator is selected followed by the design parameters or operational scenarios. To identify the interaction between parameters, in Figure 5.19 the design parameters are selected, only one design parameter will be selected in the upper part of the tool. Based on the selection, the bar plot, will be visualised. In this plot the selected design parameter is set out to all other design parameters. In the lower-part of the tool, two design parameters are selected to define the most influential combination on the selected performance indicator.

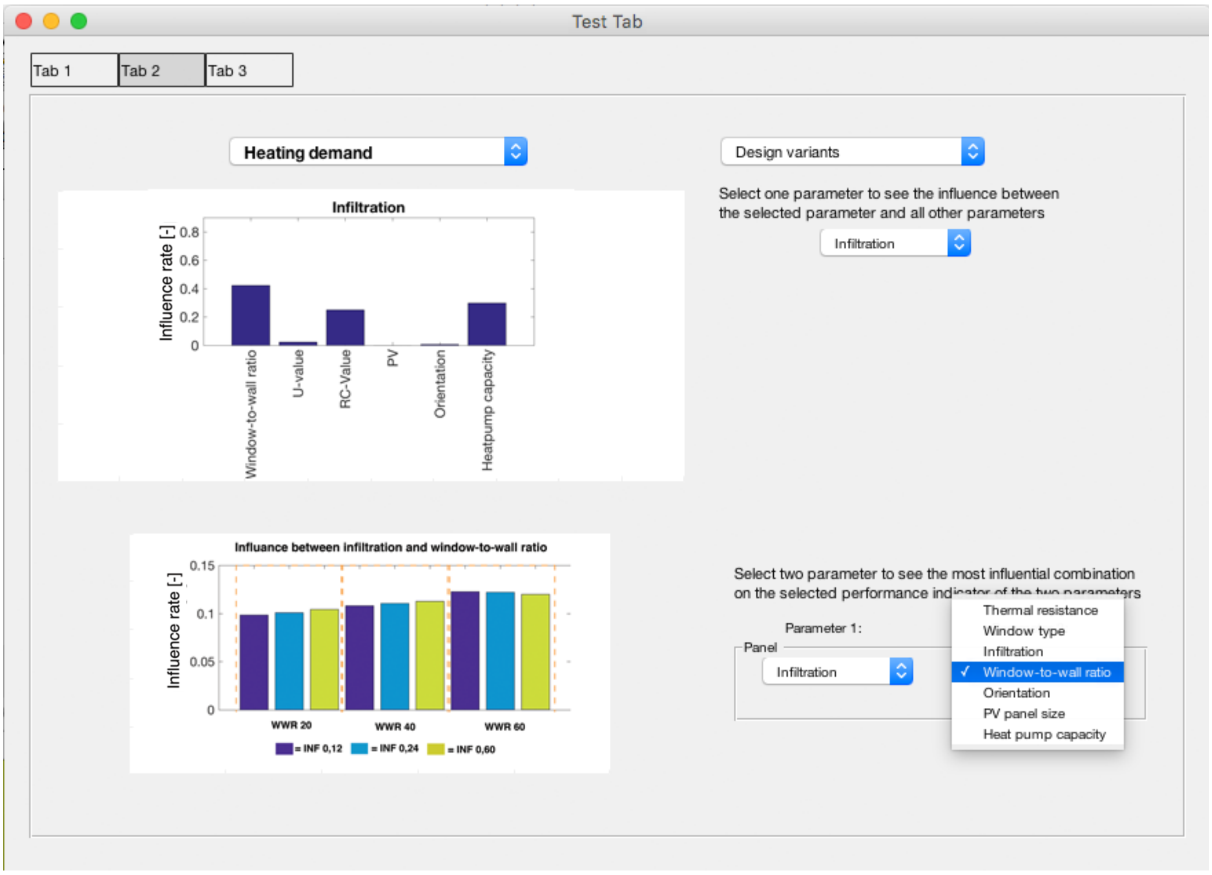

Figure 5.19 Total overview of the second tab in the tool within the upper part the visualisation of the interaction between parameters, and in the lower part the most influential combinations of two parameters.

5.5.3 Tab 3: Relation between two performance indicators based one design parameter or operational scenario

The relation between two performance indicators is visualised in a scatterplot, where one design parameter or operational scenario is selected to group the different input values, as shown in Figure 5.20. With this figure, the relation between two performance indicators can be investigated based on one parameter. This is as well possible with the parallel coordinate plot in the first tab, however, in this figure, the direction of the influence is as well visualised. As can be seen in Figure 5.20, a low

infiltration results in a low heating demand and high overheating hours. A high infiltration results in a high heating demand and low overheating hours.
The first step is selecting the design parameters or the operational scenarios. Followed by the two performance indicators. At last, the desired design parameter or operational scenario is selected to group the different values. The histograms which are shown in the graphs corresponds to the performance indicators and the different values. based on the histogram the interaction and the direction can be visualised as well.

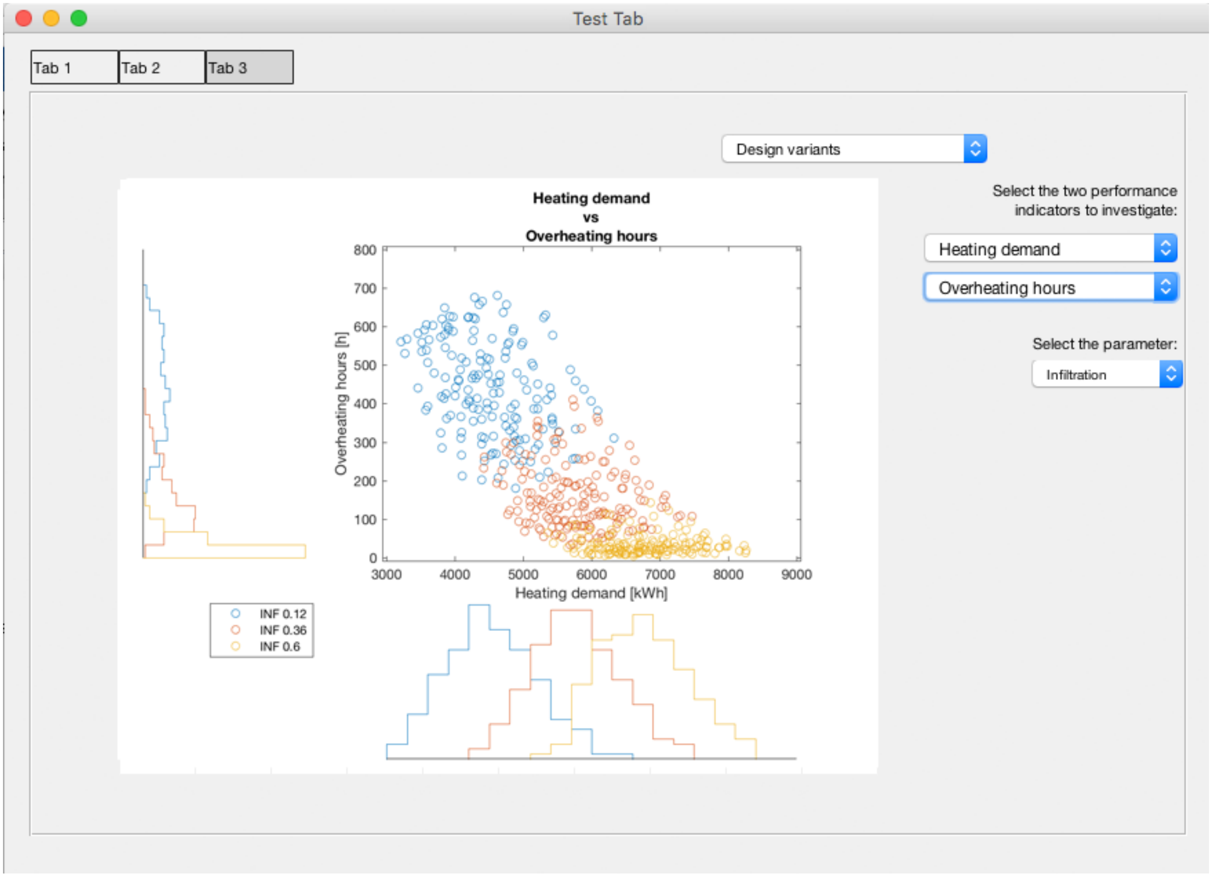

Figure 5.20 Tab 3 showing the scatterplot with the corresponding histograms where first the design variables or operational parameters is selected, followed by the performance indicators and at last the parameter.

5.6 Evaluation of the case-study results

Several methods have been used for the identification of the different interactions between the parameters and their corresponding influence on the performance indicators. The variance-based sensitivity analysis was chosen as the most suitable sensitivity analysis method to identify all the different interactions. Based on the comparison of different methods we can see that the variance-based sensitivity analysis can indeed identify the most influential parameter of different performance indicators and determine the interaction between different parameters.
The heating set-point show for every performance indicator high influences This can be explained by a human error in the Matlab script for changing the heating set-point in the building performance simulations. Due to this error, the heating set point during occupied hours for low scenario is same as that of un occupied hours and thus heating set point for this scenario is fixed at 14°C, which is supposed to be 18°C during occupied hours. This leads to large difference in heating set point during occupied

hours for low (14°C) and high scenarios (23°C).Also, the infiltration shows higher influences on the heating demand than expected. This can be explained by the heat losses. The difference between the heat losses for the lowest value of the infiltration and the highest value of the infiltration is higher than the different between the heat losses for the lowest and highest values of, for example, the thermal resistance. A more detailed evaluation of the results, including calculations, can be found in appendix J.

6 Discussion on the sensitivity analysis and the visualisation method with the stakeholder

In this chapter, the results are analysed together with the stakeholder to see if the research goal can be answered.

6.1 Information gathering method

To inform the stakeholder and gather information about the results and the visualisation tool, several methods are available. The most common methods of gathering information are [52]:

- Literature search
- Informal conversations
- Focus group
- Personal interviews
- surveys

Some information gathering methods are stage dependent. Literature search and focus group are most common in preliminary research, where all other methods can be used in all stages of a research. The purpose of the gathered information from the stakeholder is to know his opinion and eventually improve the results and the visualisation tool or make recommendations for further research. Therefore, an interactive meeting with the stakeholder in combination with a personal informal interview is chosen to inform the stakeholder about "the visualisation tool" and to receive feedback, in such way, that the tool could be implemented in a company like Kuijpers.

In this interactive meeting, the stakeholder can use the tool, get familiar with the tool, and sees the outcomes of the different results. Also, the methodology of the variance-based sensitivity analysis method is explained to the stakeholder, and why it has been chosen to determine the most influential parameters and determining the interaction between different parameters.

With the personal informal interview, several questions are asked. At first, the providence of the information of the visualisation tool in combination with the chosen sensitivity analysis methods, provides the results enough information to understand the outcomes of the methods. Second, the tool itself is questioned. Here the main questions were:

- What are the benefits of using the current tool for the stakeholder?
- How and why could the tool be implemented in a company like Kuijpers?
- What are the further improvements can be made to the tool?

6.2 The sensitivity analysis methods

The methods as explained in chapter 3 are presented to the stakeholder as well as the corresponding results shown in chapter 5. Also, the methods like the boxplot and the 3D-scatterplot as shown in chapter 5 are shown to the stakeholder. In this section the results are discussed with the stakeholder regarding the clearness and understanding of the results.

6.2.1 Most influential parameters

The results are shown based on "the visualisation tool" as explained in section 5.4. The presented parallel coordinate plot gives a clear understanding to the stakeholder about the most influential parameter of specific performance indicators. Also, it is interesting to see the development of the most influential parameters when values of a design parameter or operational scenario are varying. The difference in line colour and line-type of the design parameters or operational scenarios makes the influence on the most influential parameter understandable. A drawback is the limitation, of changing only two design parameters or operational scenarios. For the stakeholder, it would be interesting to see the most influential parameter when one or multiple design parameters or operational scenarios are set to a fixed value. The reason for this fixed value is that, in a design process, some values can be set to a fixed value during the process or based on the investigation with the tool. In the current tool, the parameters have only two or three values. For the stakeholder, it is interesting to fill in their own values to see what the impact is at the most influential parameters.

6.2.2 Interaction between parameters

The interaction between design parameters or operational scenarios and the most influential combination between design parameters or operational scenarios on a performance indicator are in the visualisation tool presented in bar plots. As mentioned in section 5.4, these two methods are split into two parts. Looking to the interaction between parameters, the bar plot provides enough information to identify the interaction between parameters. The stakeholder is informed about the differences between the values, when comparing the values of parameter i to parameter j and parameter j to parameter i as shown in Figure 5.11. An alternative for this is taking all possible interactions between design parameters or operational scenarios into account. However, a bar plot is due to the many possibilities between the parameters or scenarios not possible. A table could be implemented to give the different values.

The visualisation of the most influential combination of two design parameters or operational scenarios on a performance indicator is hard to understand for the stakeholder. When explaining the bar plot how to read it, it is clear about the purpose of the bar plot however, it could be simplified. The 3D-scatterpot method as explained in section 5.2.3 is easier to understand and has more benefits for the stakeholder. Al outputs of all simulations are visualised in the 3D-scatterplot where the outputs are categorised based on the input values of the two chosen design parameters or scenarios. In 3D-scatterplot, the minimum and maximum value of specific input values of the two selected design parameters or scenarios can be found. For the stakeholder, this is much more interesting when discussing the results with a third party and showing the effect of changing an input value in a specific parameter. Therefore, the stakeholder recommends changing the bar plot into the 3D-scatterplot resulting in Figure 6.1.

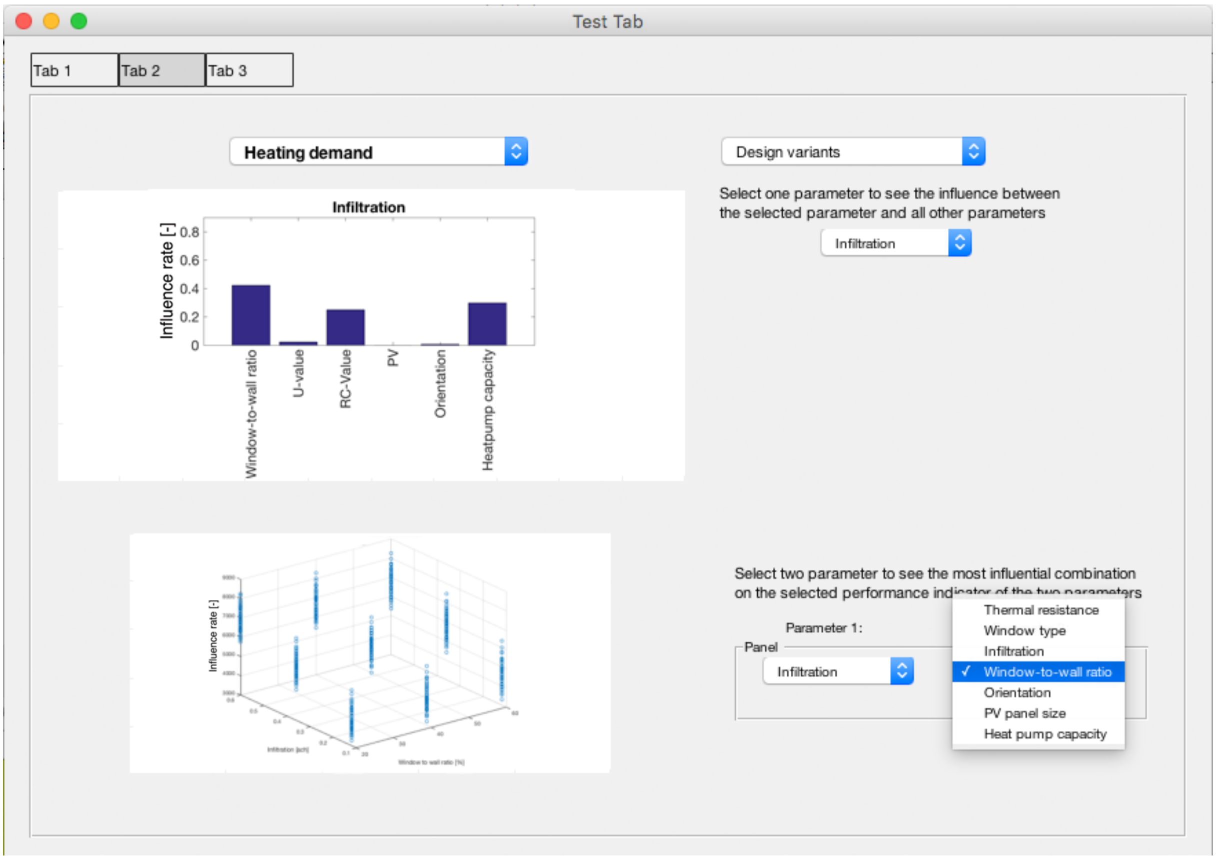

Figure 6.1 Tab 2 of the visualisation model when changing the bar plot of the most influential combination to the 3D-scatterpot.

6.2.3 Relation between the performance indicators

The relation between the performance indicators as shown in Figure 5.20 gives a clear overview of the direction of the influence of different design parameters and operational scenarios. The outcome is easy to understand and easy to handle. In combination with the other tabs, especially with tab one, it has a great possibility of enhancing the decision-making process but as well informing other persons who are not familiar with the tool.

6.2.4 Overall interpretation of the used methods

Based on the answers of the stakeholder, the variance-based sensitivity is implemented well. The results what are shown gives a clear overview which parameters have the most influence on a performance indicator and which parameters have the strongest interactions between each other. Regarding the outcome of the simulations, the stakeholder would like to compare the outcome of the simulations with other building performance simulation tools like, for instance, Vabi elements to validate the outcome of the TRNSYS models. In addition, the stakeholder would like to see the influence when extreme values are implemented. All parameters have now realistic values, where the stakeholder is also interested in extreme values to see if the used method is applicable.

6.3 The visualisation tool

The visualisation tool as explained in appendix I is built in Matlab and presented to the stakeholder. The advantage of using Matlab is that the total design of the visualisation tool can be designed to the requirements of the user and can be changed to the requirements of the user.

6.3.1 Benefits of the tool.

According to the stakeholder, the presented tool is a simple one and easy to use. The tool can be easily implemented during meetings with third parties to show the effect on several performance indicators when changing the parameters. Therefore, the tool can support important design decisions for both parties. The setup of the tool has a clear and structured overview, which makes it easy to work with.

6.3.2 How and why could the tool be implemented in a company like Kuijpers?

For implementing the current tool in a company like Kuijpers adjustments should be made. The tool presented now is a good base for further research and extending the tool itself. In the current tool, the essence of finding the most influential parameters and the interaction between parameters is captured. To implement the tool in a company like Kuijpers more parameters, performance indicators and options should be implemented. Also, it could be interesting to connect the visualisation tool to other building performance simulation tools, which is doable. For Kuijpers it would be interesting to make the tool in such way that it is possible to connect Vabi elements (currently used at Kuijpers) or other building performance simulation tools.
At last to integrate the tool in the work process a clear and detailed guide should be written or a course should be given to enhancing the use of the tool to get all personnel familiar with the tool.

6.3.3 How to improve the tool

The tool as it is presented today is a basic version what could be extended in different ways to improve the tool and to enhance the design decision-making process. As already mentioned, it would be interesting to implanting more parameters and variables in the tool for instance; the building shape and dimensions and the load duration curve. For the stakeholder, it is as well interesting to save settings, set fixed values to different parameters when these are already defined in the design process or to implement own values by using a slide bar or a fill-in field.

Also, the stakeholder finds it interesting to go more into detail. For example, analysis at zone level instead of total building. Also, it would be interesting to go more into detail by defining different parameter based on the orientation or size of the building. For example, changing the window-to-wall ratio on a specific façade when window-to-wall ratios of the remaining facades remains the same to investigate the effect on the performance indicators of changing these specific parameter values.

7 Conclusion & Recommendations

7.1 Conclusion

The aim of this research is to enhance the design decision-making process by investigating the influence and interaction of different design parameters and operational scenarios on different performance indicators, and visualise these results to enhance communication. To reach this goal, several objectives have been established with the main objective to develop a method/ tool which shows different visualisation methods in such way, that it enhances the design decision-making process.

The first and second objectives are to investigate sensitivity analysis methods and visualisation methods to define the most influential parameters and the interaction between different parameters. For this research, the variance-based sensitivity analysis has been used based on literature review. The benefit of using the variance-based sensitivity analysis is that it can attribute the variance of a model output to each parameter, it can show the interaction on the sensitivity between the parameters and it can take the scale and shape of the input parameters into account. For visualisation of outcomes of sensitivity analysis, several visualisation methods have been used. For instance, bar plots and parallel coordinate plots are multidimensional scaling methods where the similarity between individual input data is compared. The parallel coordinate plots are mostly used for high dimensional data. In this project, the parallel coordinate plot is used to improve the visualisation of multiple bar plots together, as explained in Figure 3.7.

The last objective was to apply the selected sensitivity analysis method on the net-zero energy building to investigate the most influential design parameters and assess the impact of the design parameters on performance indicators. The selected sensitivity analysis method, in combination with different visualisation methods, shows that infiltration is the most influential design parameter for the heating demand and the over-heating hours, whereas window-to-wall ratio, PV panel size and thermal resistance are the most influential design parameters for the total cost of ownership. Heating set point is the most influential operational scenario for all considered performance indicators, considering that for this operational scenario there is an input error. The next most influential operational scenarios are for the heating demand, overheating hours and the total cost of ownership the number of occupants and ventilation.

The direction in where the influence takes place cannot be visualised in the variance-based sensitivity analysis methods. The bar plot and the parallel coordinate plots both gives the percentage of the variances. However, these two plots do not represent the lowest and highest value. Therefore, the scatterplot is added to investigate the direction of the influence and the relation between two performance indicators with respect to a design parameter or operational scenario. In these figures, the direction of the influence can be found by looking at the corresponding histograms. Each design parameter or operational scenario is grouped based on their value, where each performance indicator value can be found on the histogram. The peak in the histograms indicate the amount of values of that specific value of the selected parameter. The spread of the different peak values indicates an interaction, as well as the direction of the values.

The main objective of this research was to develop a tool which shows different visualisation methods in such way that, it enhances the design decision-making process of a stakeholder. The tool designed for this research is an easy to understand and clear tool what captures the essence of finding the most influential parameter and the interaction between parameters. For the stakeholder, improvements can be made by connecting the tool to different building performance simulation tools or design the tool in such way that multiple building performance simulation tools could be implemented. Also, connecting the visualisation tool to a building performance simulation tool in such way that given values like parameters, building shape, building size, can be implemented. At last, going into detail is of great interest to give a more insight of the influence on different performance indicators regards different sections, parts and levels of the building.

The overall aim of this project was to enhance the design decision-making process by investigating the influence and interaction of different parameters and showing these results in easy visualisation methods. As can be concluded based on the objectives, it is possible to identify the most influential parameters, and the interaction between different parameters by using the variance-based sensitivity analysis. The bar plot in combination with the parallel coordinate plot and the scatterplot can show these interactions. The tool developed for visualising the results in an interactive way is easy to understand and easy to use. However, the use of the selected sensitivity analysis has large simulation time, what should be considered when choosing this method. As well, the visualisation tool now is only a concept version. Improvements should be made to the visualisation tool for a more detailed interpretation of the influence on the building.

7.2 Recommendations

Further research can be conducted on the following points.

- Implementing the possibility of using multiple or another building performance simulation tool in the visualisation tool.
- Extend the GUI by implementing:
    - Load duration curve
    - The interactions between all parameters
    - The possibility of implementing own values for parameters
    - The possibility of investigating sections of the building on building level, but as well on façade level.
    - The possibility of implementing the geometry of the building in the visualisation tool, and separate these from the investigation of other parameters. In short, defining the building shape in the visualisation tool and based on that shape identifying the most influential parameter and the interaction between different parameters

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Appendix A

The pooled variance can be estimated by the weighted average. The weighted average calculates the average of the values where the highest numbers has the most influence on the outcome.
The weighted average is given by the formula [53][54]:

$$\bar{x} = \frac{\sum_{i=1}^{n} g_i x_i}{\sum_{i=1}^{n} g_i} \qquad \text{(A.1)}$$

where:
$x_i, \ldots, x_n$ = Numbers
$g_i, \ldots, g_n$ = Weighted values

the variance is calculated by the formula [55]:

$$s^2 = \frac{1}{N-1} \sum_{i=1}^{N} (x_i - \mu)^2 \qquad \text{(A.2)}$$

μ = Population average
s^2 = Population variance
N = Population size
x_i = Population elements

combining the variance and the weighted averages the pooled variance can be denoted as [54]:

$$V_i = s_p^2 = \frac{\sum_{i=1}^{k} (n_i - 1) s_1^2}{\sum_{i=1}^{k} (n_i - 1)} \qquad \text{(A.3)}$$

where:

$$s_1^2 = \frac{1}{N-1} \sum_{j=1}^{n_i} \left(y_j - \bar{y}_J\right)^2 \qquad \text{(A.4)}$$

s_1^2= variance of the difference of design parameter X_i

Appendix B

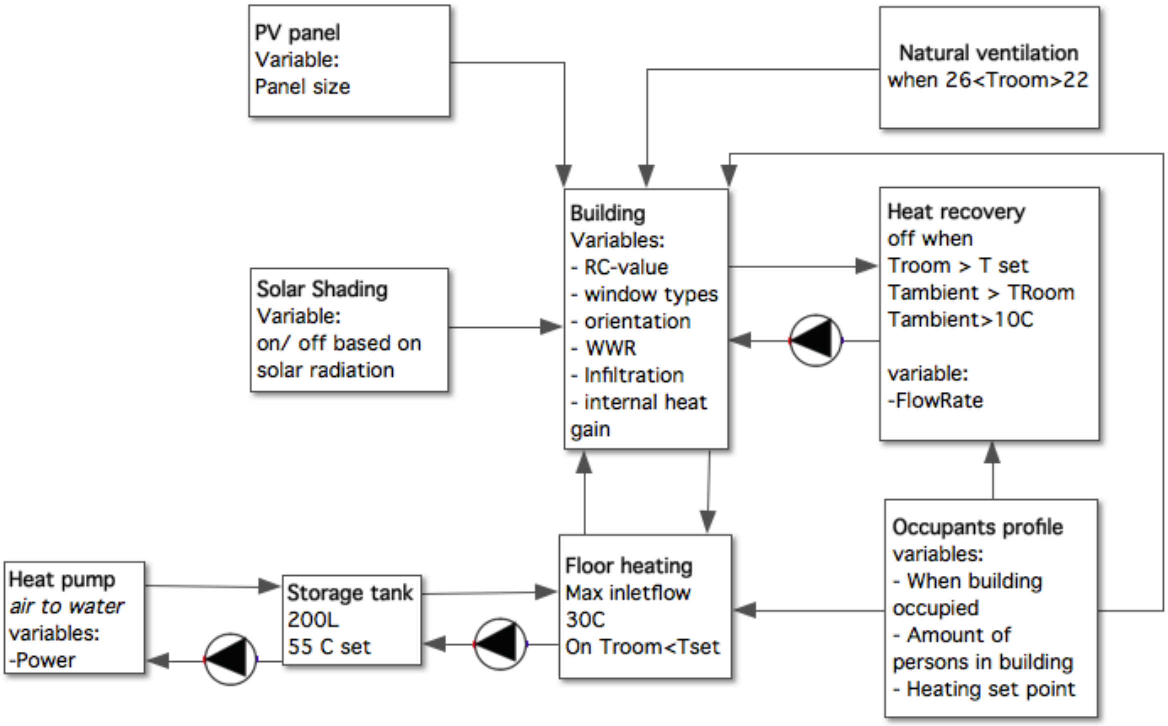
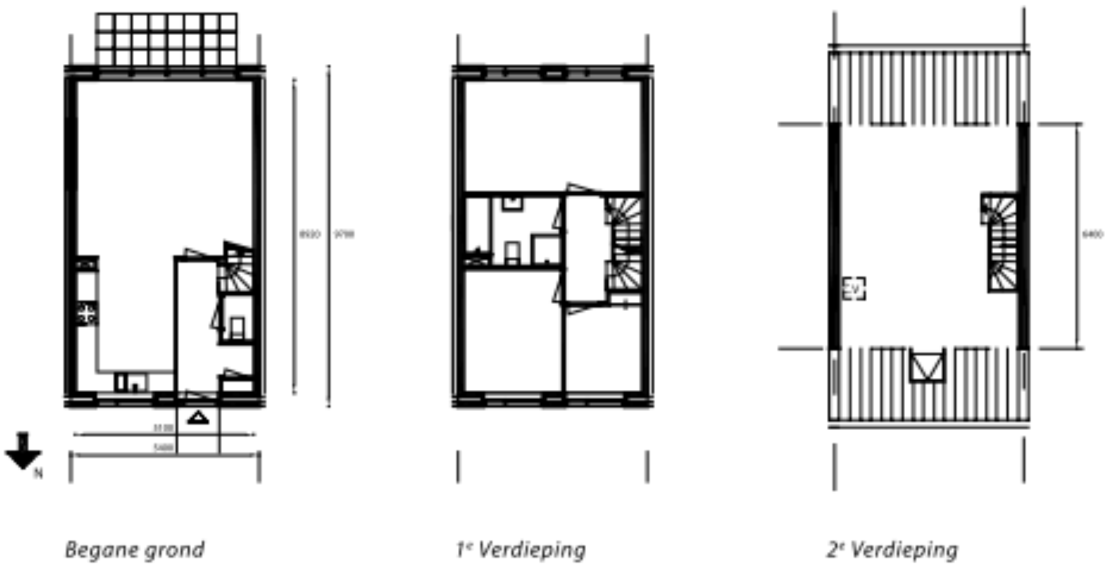


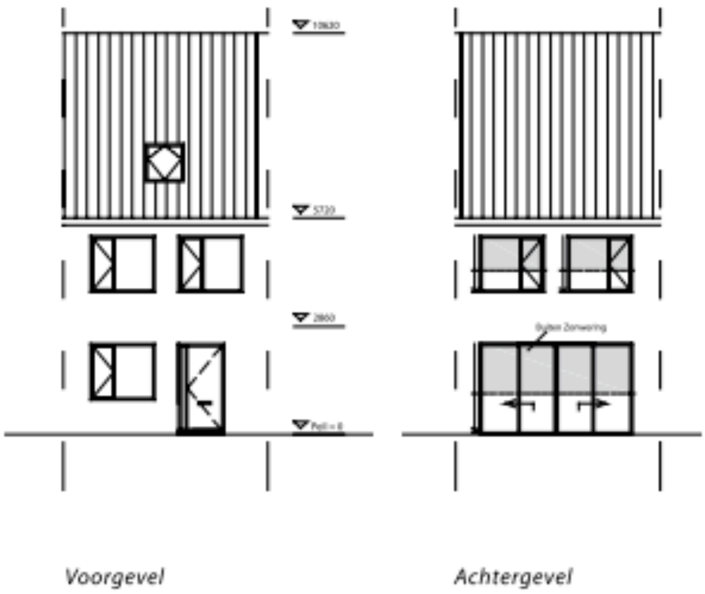
Figure 1 Schematic overview of the TRNSYS model of the case-study building including the variables

Appendix C

Reference building description

The used geometric building shape of the reference building is described in 'Agentschap NL referentiewoningen 2013' [37] although, there is more space reserved for installations. The reference building has a used surface area of approximately 130 m^2 and a loss surface area of about 175 m^2. Living room and kitchen constitute the ground floor, three bedrooms on the first floor and an attic on the second floor. The south façade has a large window on the ground floor and all bedrooms have windows of the same size. The dimensions of the building are [36]:





Floorplan:	9m x 5m
Building height:	2.6m
Windows:	1.6m x 1.8m
Bay window:	4.0m x 2.4m
Roof window:	1m x 1.2m
Door:	1.0m x 2.4m

Figure 4.1. building case dimensions [37]

Thermal requirements & installations

Building requirements

The building thermal requirements are given in table 4.1 [2] [4] [5].

Table 4.1. Building requirements reference building

Building requirements	
Rc-value Floor	5.0 m^2K/W
Rc-value Wall	6.0 m^2K/W
Rc-value Roof	7.1 m^2K/W
U-value Window	0.86 W/m^2K
g-value Window	0.6
Infiltration	0.08 ACH
Automatic solar shading ON	200 W/m^2
Automatic solar shading OFF	250 W/m^2
Weather	"de Bilt"

Installation requirements

Regards installations, the following values are considered for the reference building and are given in table 4.2 [2] [4] [5] [42].

Table 4.2. Installation requirements reference building

Installation requirements	
Heat pump	COP 3.5
	H capacity 7.5 kW
	H power 2.14 kW
Floor heating	T difference of 5°C inlet outlet
Fluid flow	800 Kg/hr
Heat recovery system	Off when: $T_{indoor} > T_{heating\ setpoint}$
	$T_{ambient} > T_{indoor}$
	$T_{ambient} > 10°C$
Mechanical ventilation	Ground floor 1.7 ACH
	Floor 1 1.4 ACH
	Floor 2 0.7 ACH
Natural ventilation	On when $22°C < T_{indoor} < 26°C$
Heating set point occupied	23°C
Heating set point unoccupied	18°C

The mass flow of the floor heating system and the heat recovery system are defined by the following formulas:

$$\dot{Q} = \dot{m} \cdot C_p \cdot \Delta\theta \quad (4.1)$$

$\dot{Q}$ = Capacity [kW]
$\dot{m}$ =mass flow rate [kg/s]
C_p =Specific heat capacity [J/kgK]
$\Delta\theta$ =Temperature difference [°C]

$$\dot{m} = V \cdot C_p \cdot ACH \quad (4.2)$$

$\dot{m}$ =mass flow rate [kg/s]
V = Volume [m^3]
C_p =Specific heat capacity [J/kgK]
ACH =Air change per hour [1/h]

The heating capacity and the heating power of the heat pump are defined by:

$$COP = \frac{heating\ capacity}{heating\ power} \tag{4.3}$$

COP = Coefficient of performance

According to (Tennokese et al., 2013) the coefficient of performance usually has a value between 2.5-4.5 [42]. Therefore, the coefficient of performance (COP) of the heat pump in the reference building is set to 3.5.

Appendix D1

Design parameters

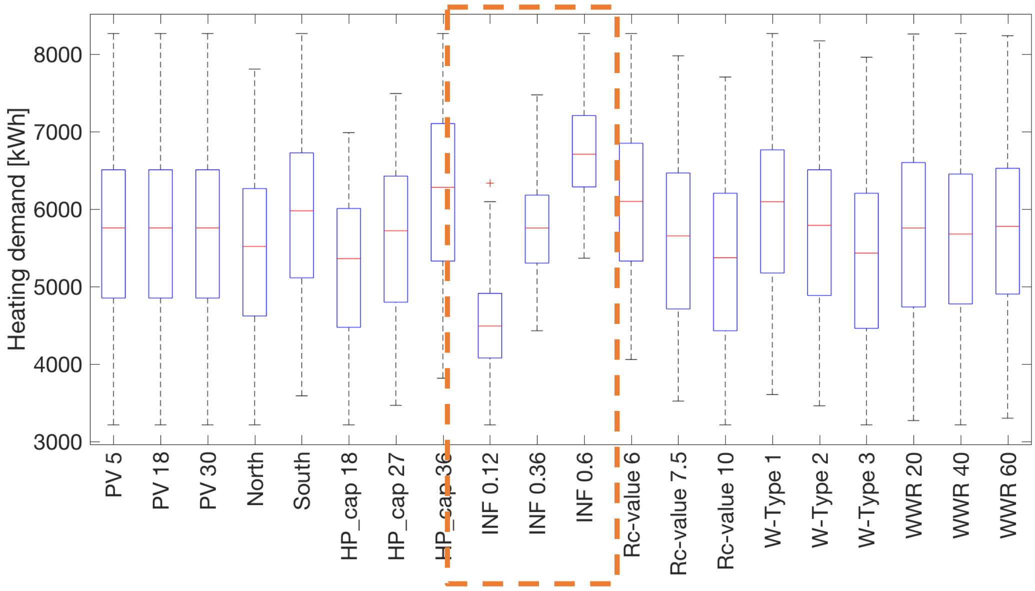


Figure D1-1 Boxplot of the heating demand of different design variables.

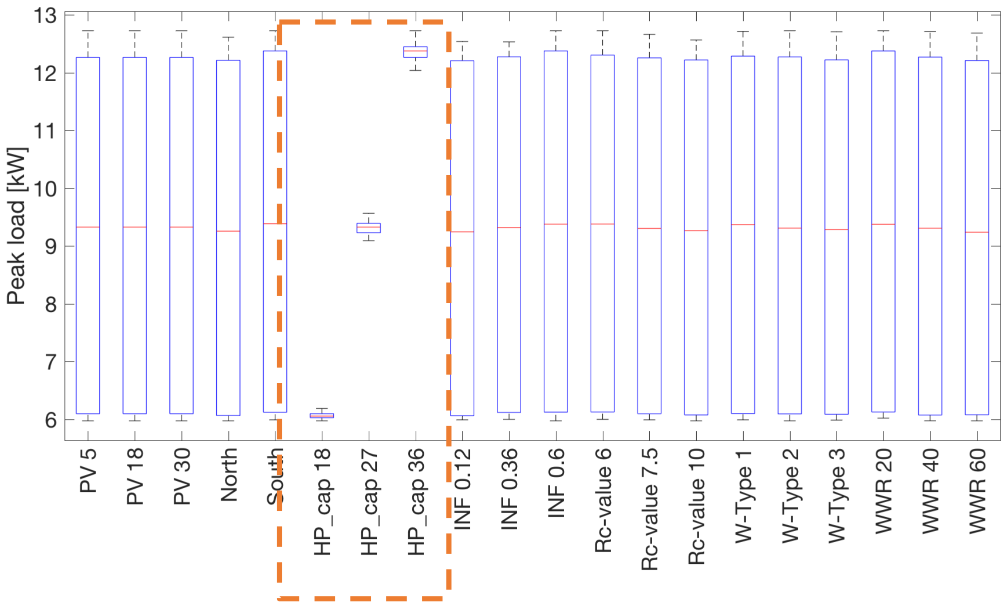


Figure D1-2 Boxplot of the Peak load of different design variables.

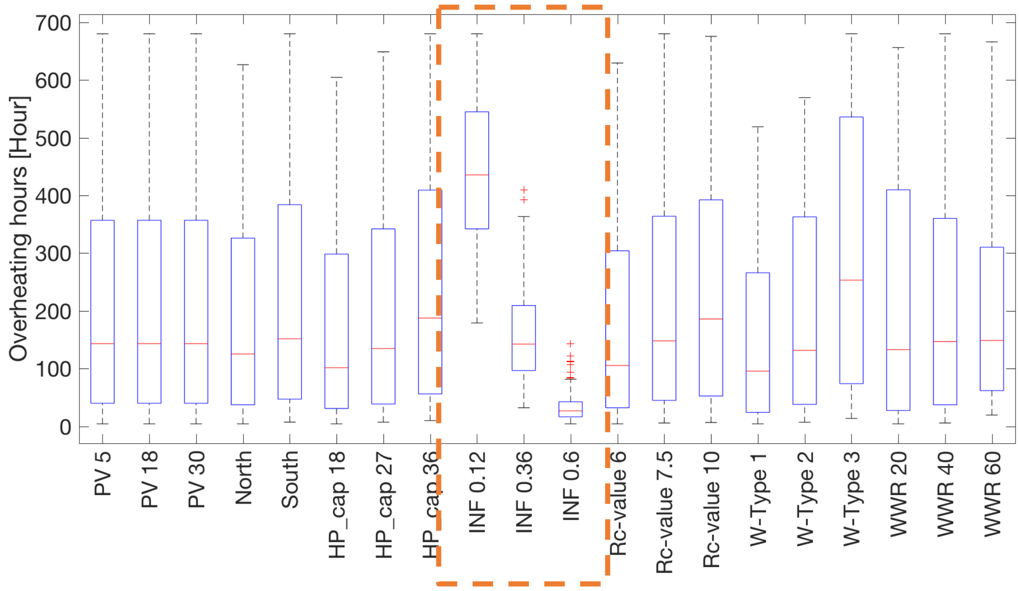


Figure D1-3 Boxplot of the overheating hours of different design variables.

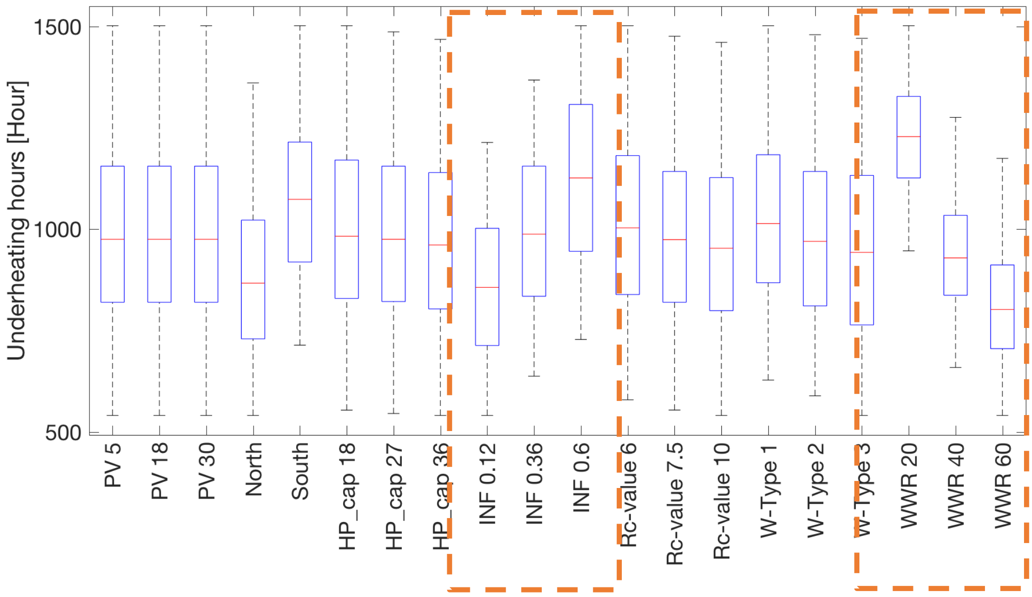


Figure D1-4 Boxplot of the under-heating hours of different design variables.

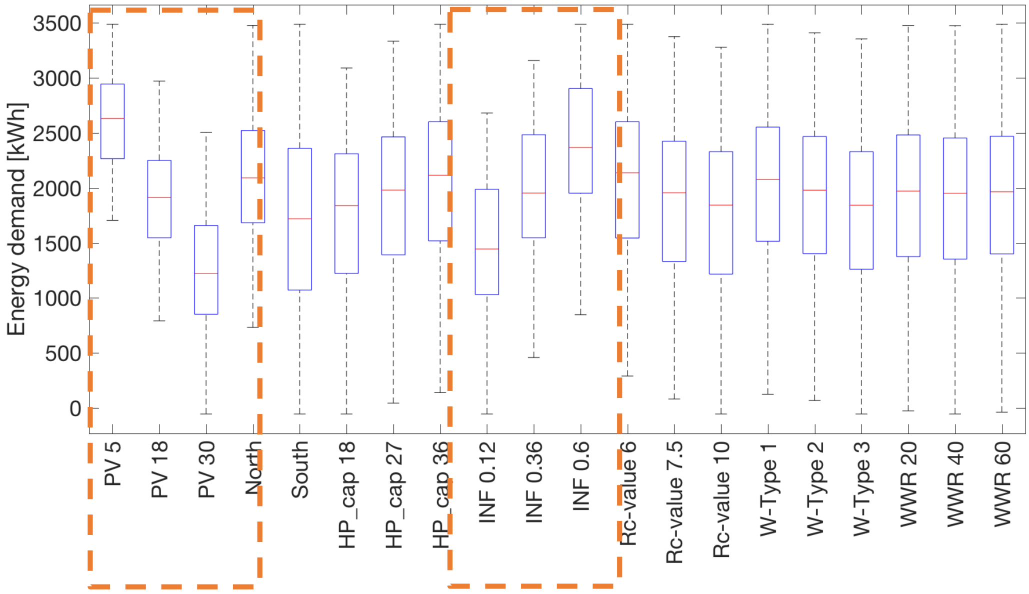


Figure D1-5 Boxplot of the net energy demand of different design variables.

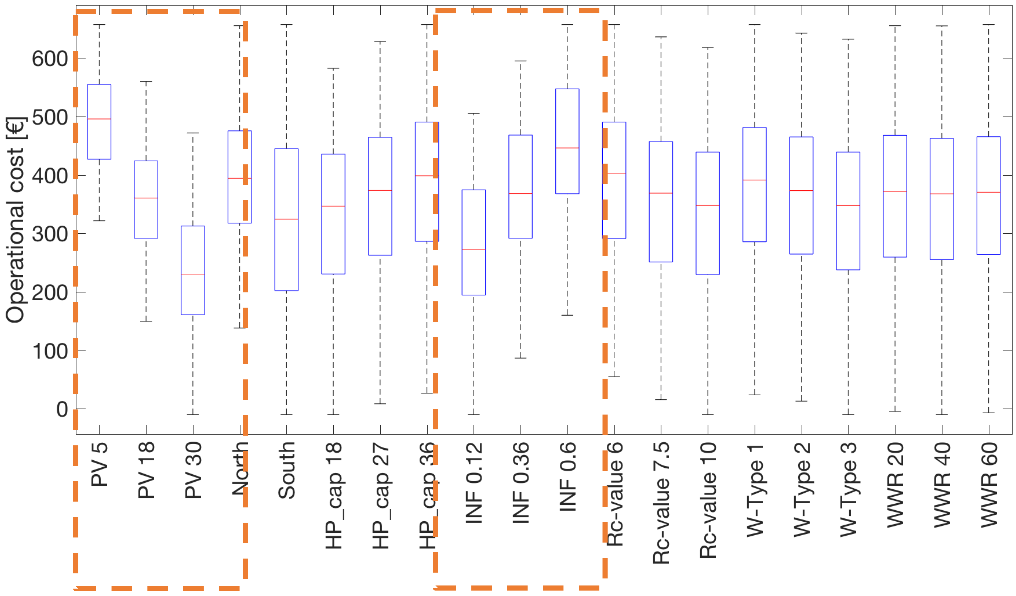


Figure D1-6 Boxplot of the operational cost of different design variables.

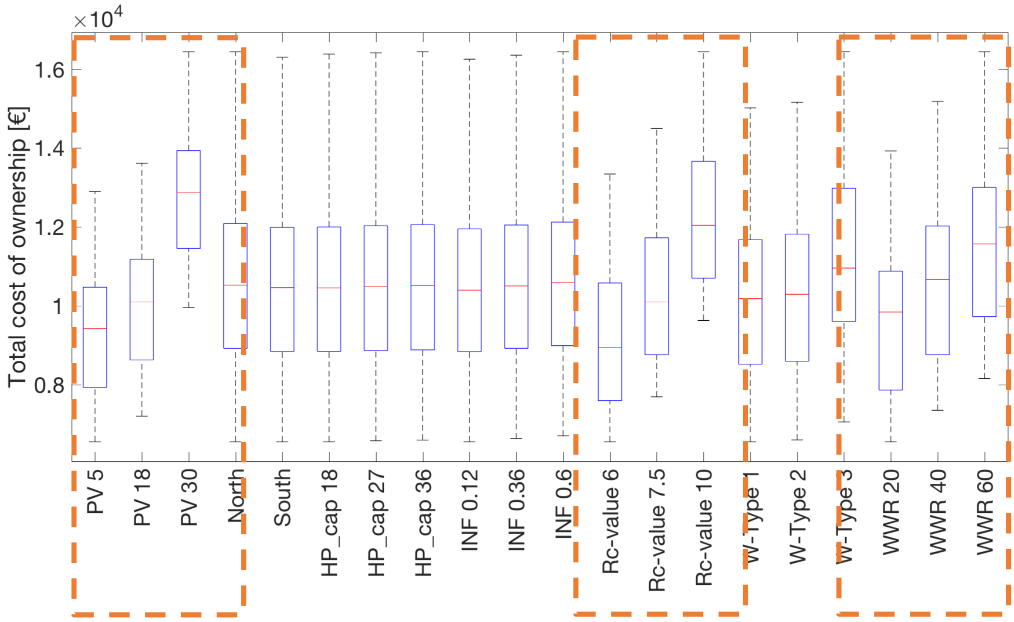


Figure D1-7 Boxplot of the total cost of ownership of different design variables.

Appendix D2

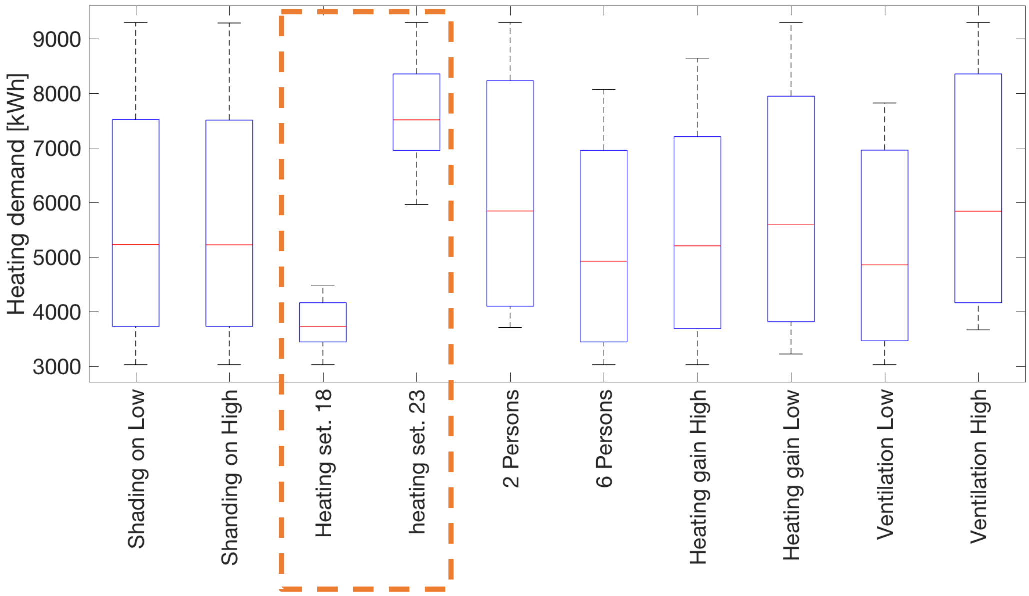


Figure D2-*1 Boxplot of the heating demand of different design variables.*

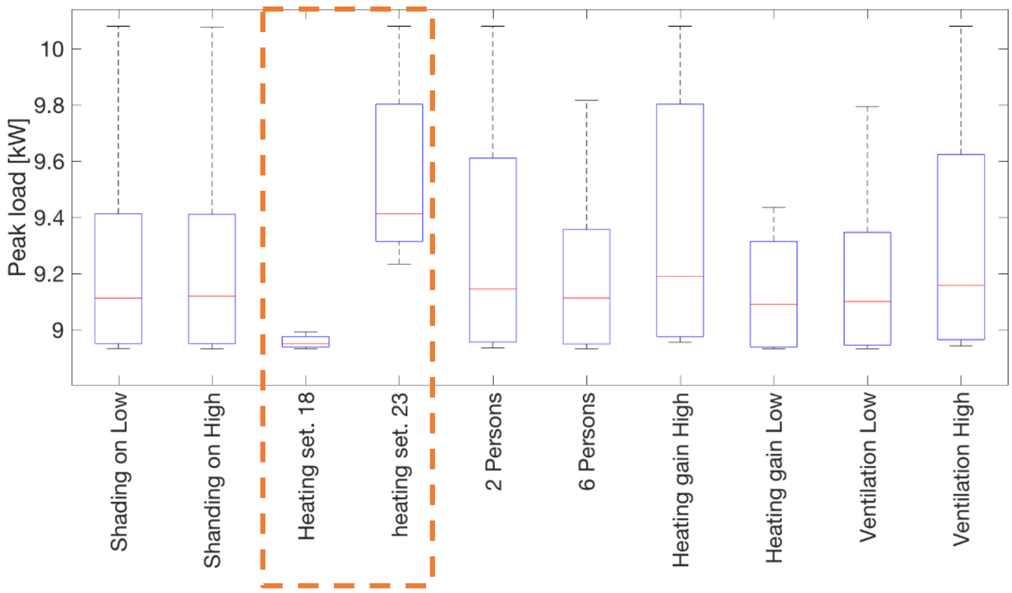


Figure D2-*2 Boxplot of the peak load off all different design variables.*

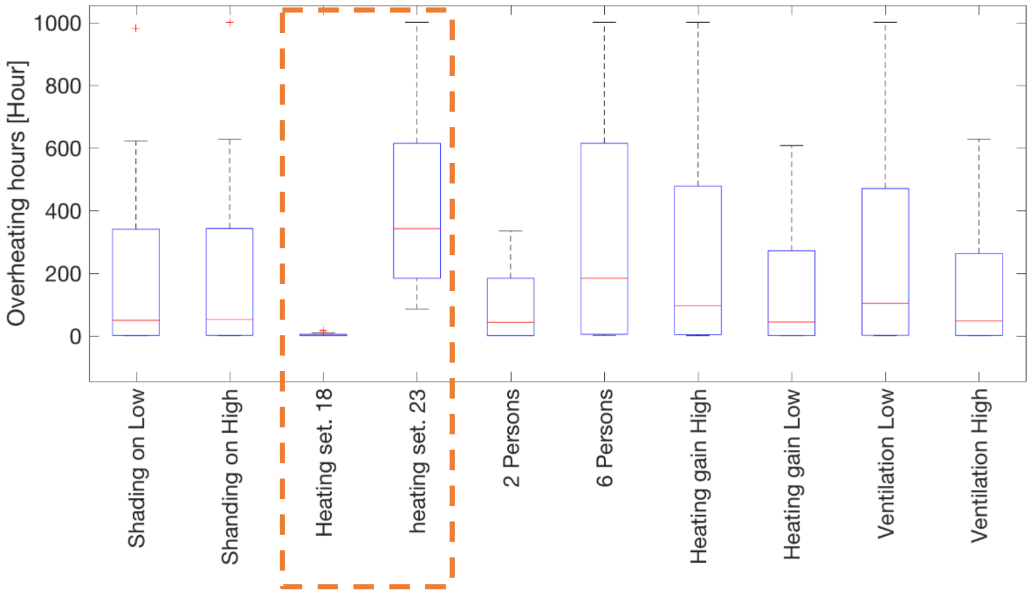


Figure D2-*3 Boxplot of the Overheating hours off all different design variables.*

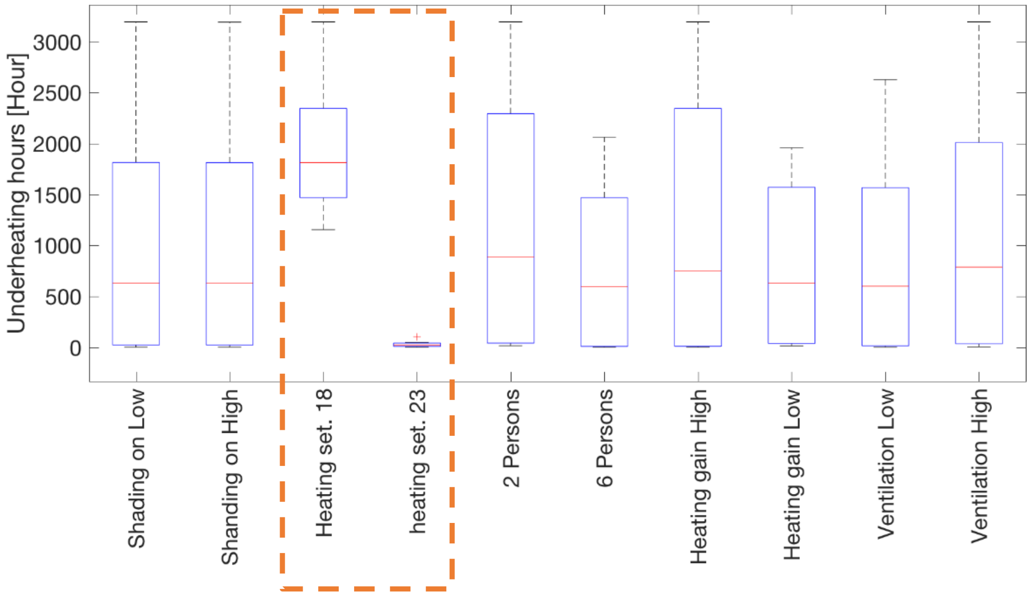


Figure D2-*4 Boxplot of the Under-heating hours off all different design variables.*

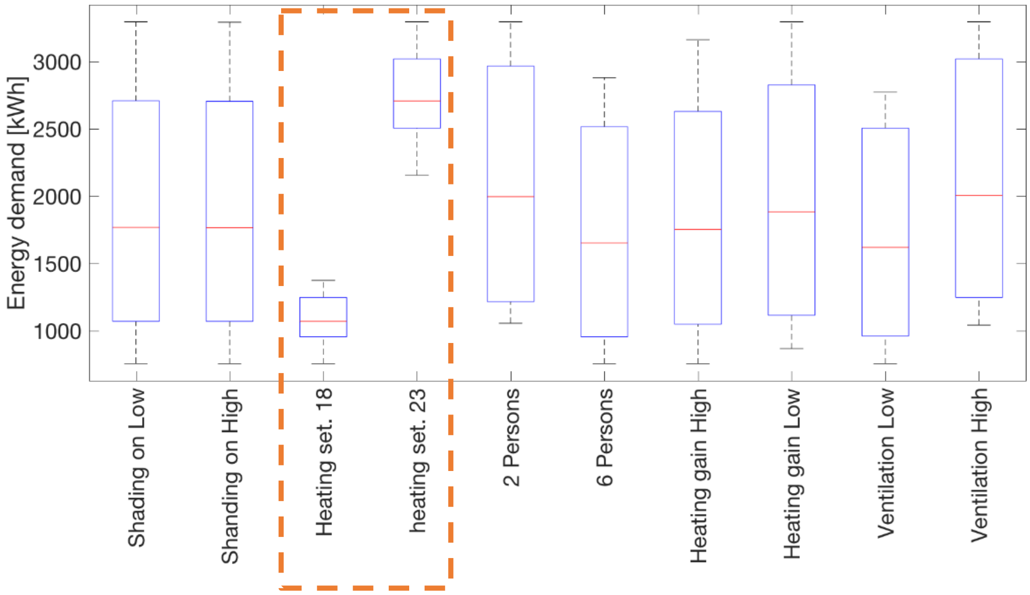


Figure D2-*5 Boxplot of the net energy demand off all different design variables.*

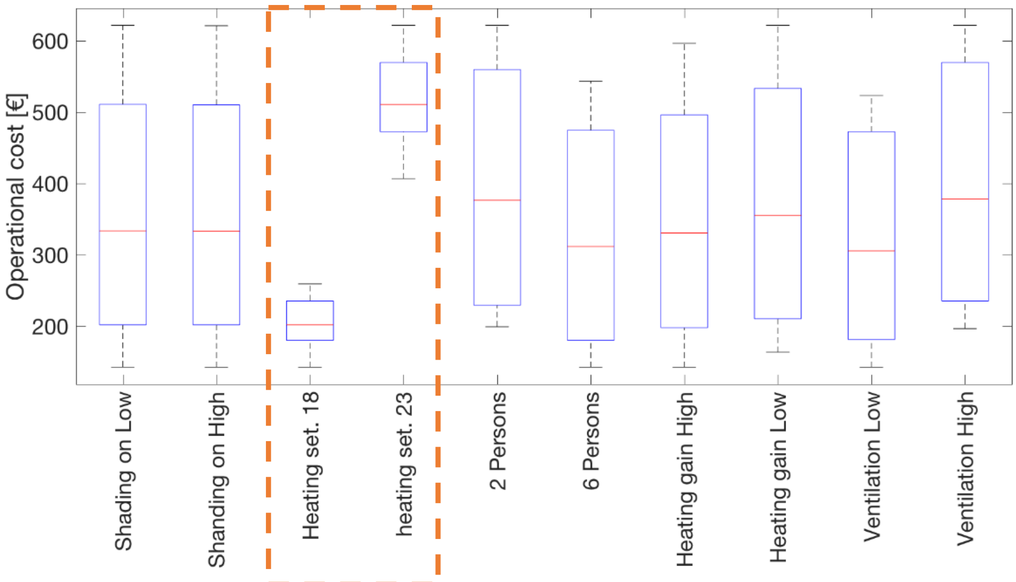


Figure D2-*6 Boxplot of the Operation cost off all different design variables.*

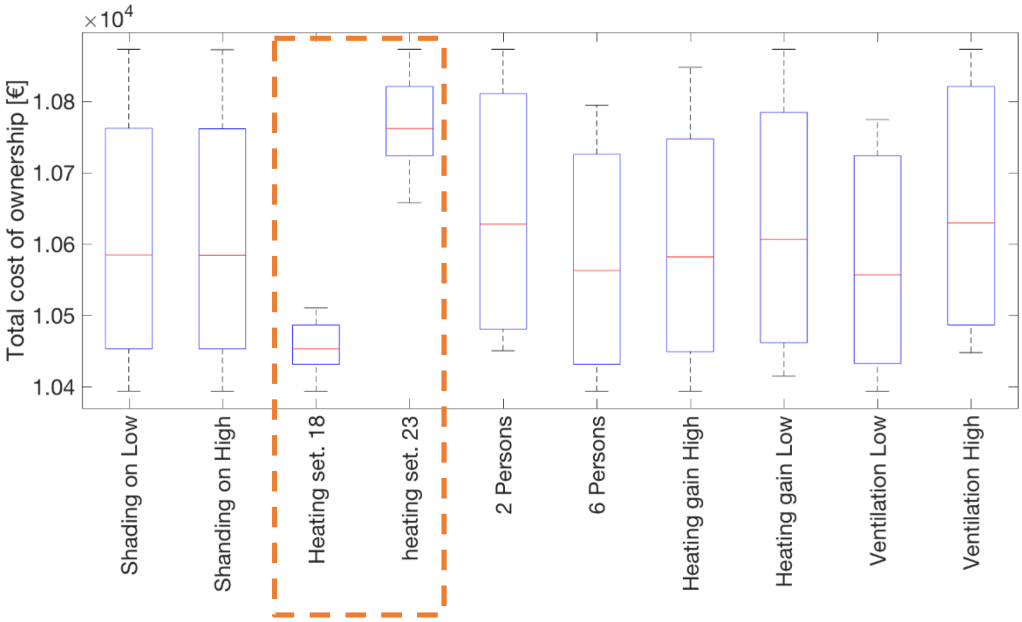
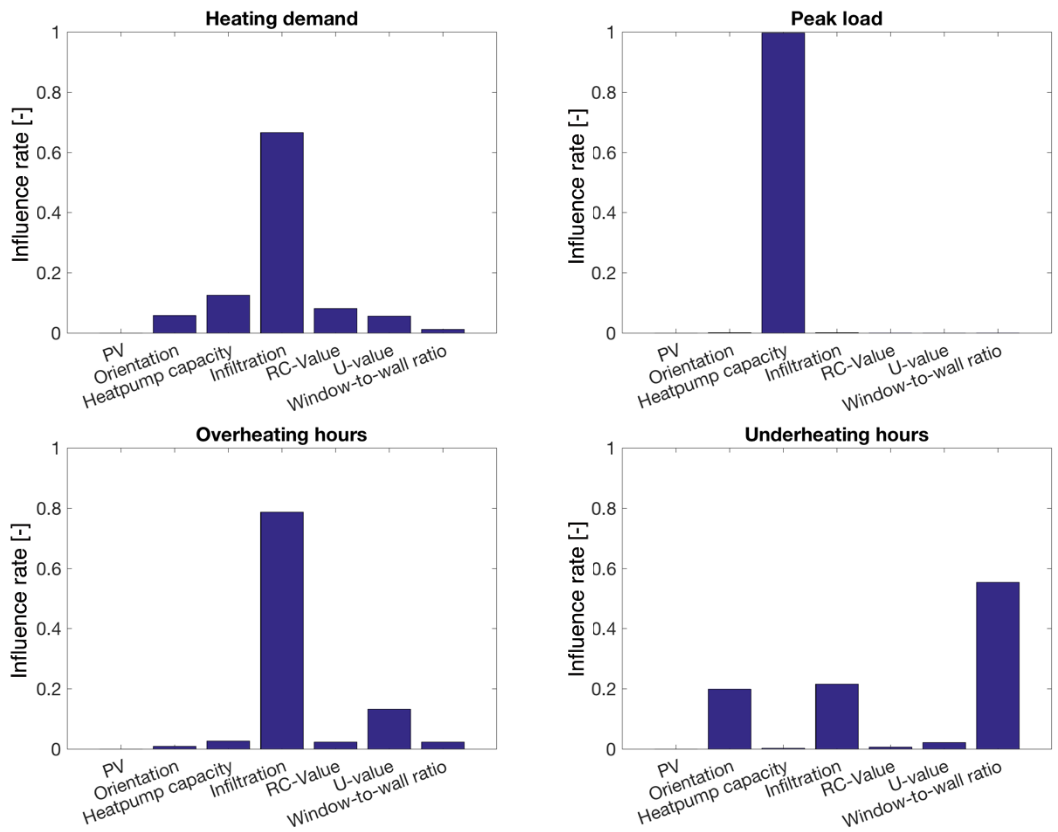


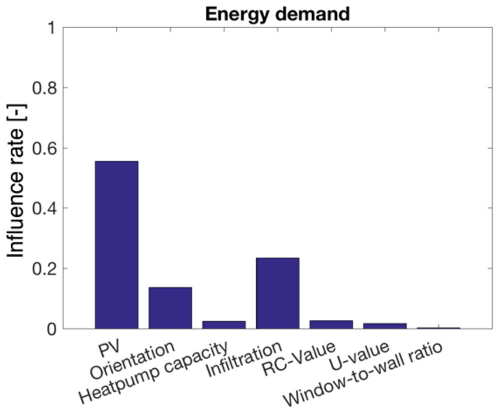
Figure D2-*7 Boxplot of the Total cost of ownership off all different design variables.*

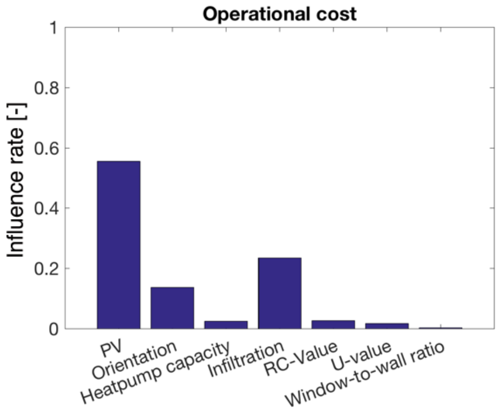
Appendix E

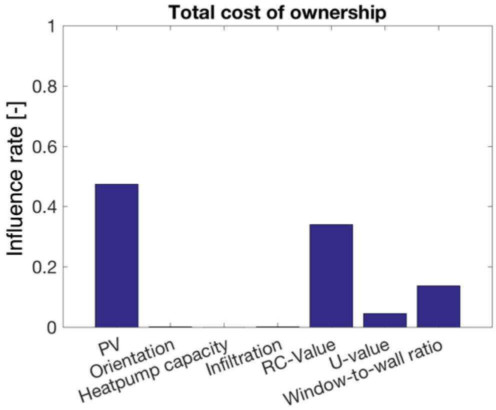
This appendix gives an overview of all performance indicators and their most influential parameters. As can be seen, for the design parameters, the PV size has the most influence on the net energy demand, operational cost and total cost of ownership. The peak load is only influenced by the heat pump capacity and the under-heating hours is the most influenced by the window-to-wall ratio. The infiltration has, as already mentioned, the most influence on the heating demand and as well on the over-heating hours. Regards the operational scenarios, the most influential parameter of all the performance indicators is the heating set-point. The number of occupants in the building is the second highest most influential parameter for the overheating hours where the internal heating gains the second highest most influential parameter of the peak load. The net energy demand, operational cost and total cost of ownership have all the same values of influence rate. This could indicate that all changes what are made in one parameter will influence all performance indicators equally.

Design parameters

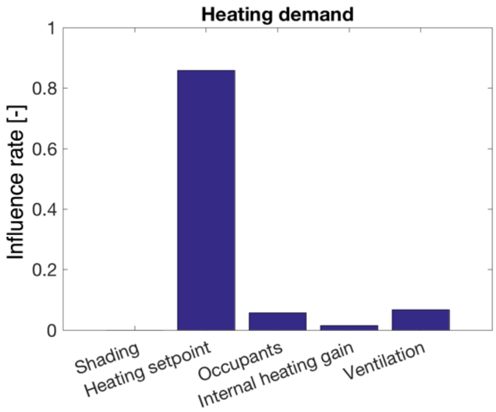


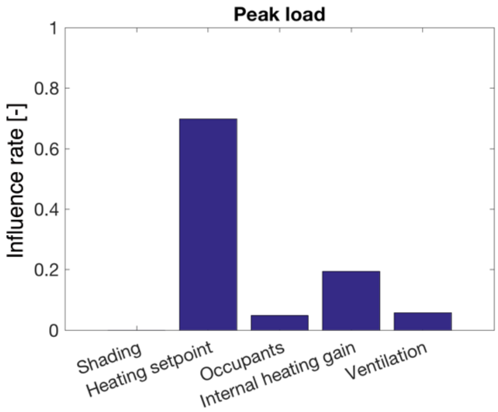


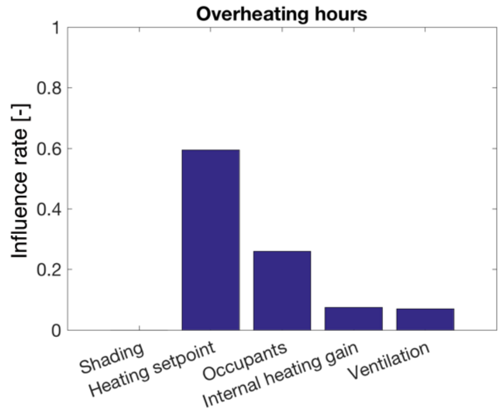


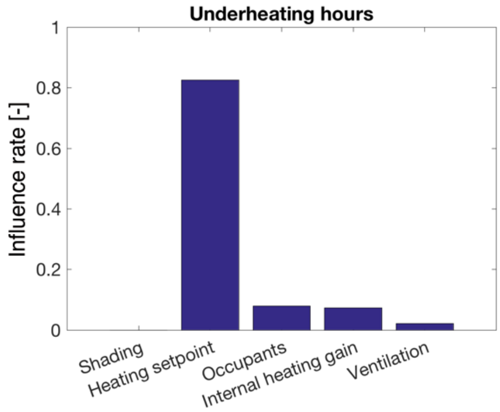


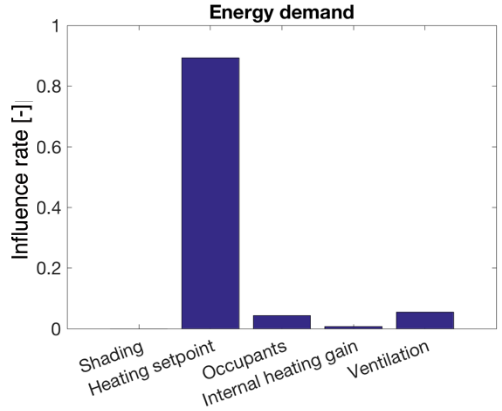
Operational scenarios






Overheating hours
Influence rate [-]
1
0.8
0.6
0.4
0.2
0
Shading
Heating setpoint
Occupants
Internal heating gain
Ventilation


Underheating hours
Influence rate [-]
1
0.8
0.6
0.4
0.2
0
Shading
Heating setpoint
Occupants
Internal heating gain
Ventilation


Energy demand
Influence rate [-]
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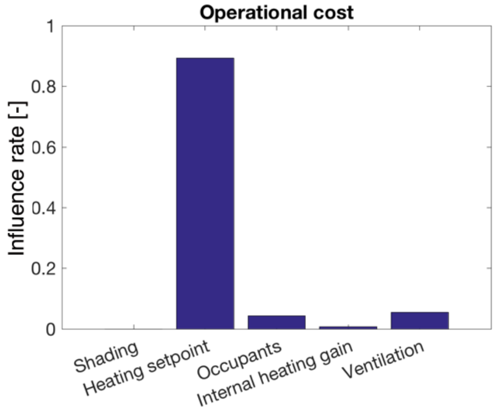
0.8
0.6
0.4
0.2
0
Shading
Heating setpoint
Occupants
Internal heating gain
Ventilation


Operational cost
Influence rate [-]
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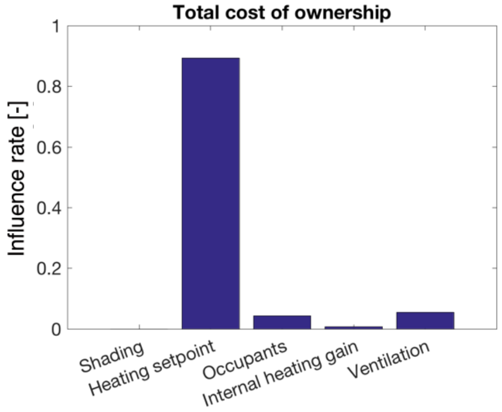
0.8
0.6
0.4
0.2
0
Shading
Heating setpoint
Occupants
Internal heating gain
Ventilation


Total cost of ownership
Influence rate [-]
1
0.8
0.6
0.4
0.2
0
Shading
Heating setpoint
Occupants
Internal heating gain
Ventilation

Appendix F1

Design parameters

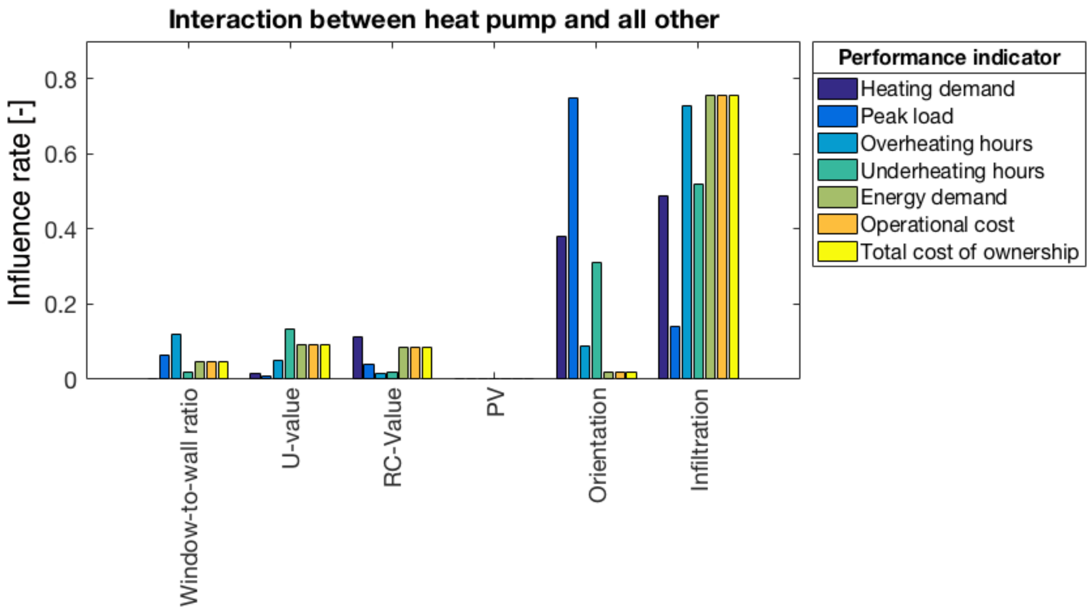


Figure F1-1 Interaction between the heat pump capacity and all other parameters over all the performance indicators

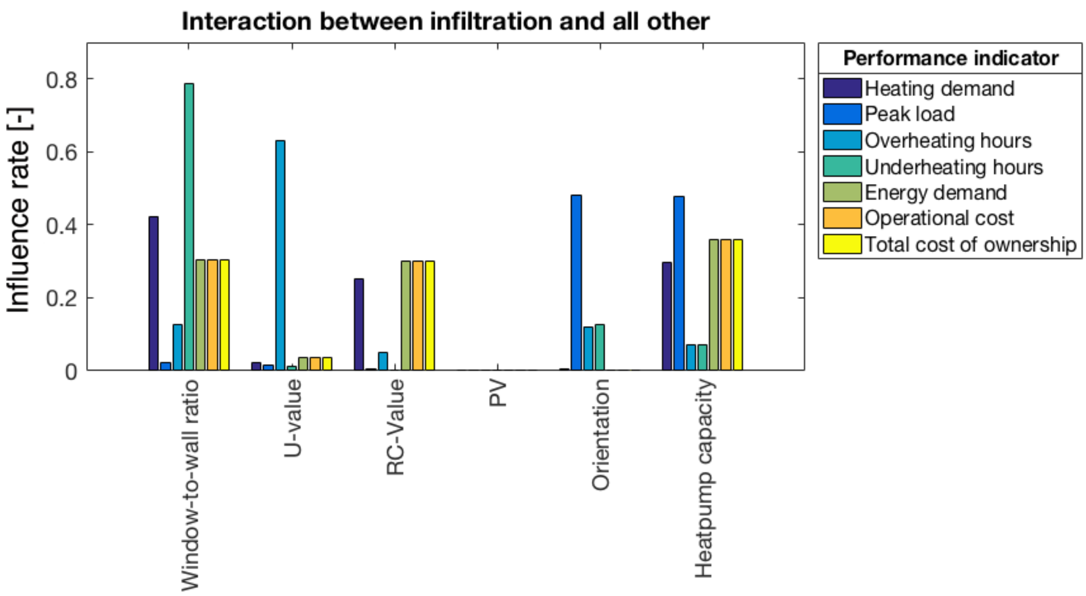


Figure F1-2 Interaction between the infiltration and all other parameters over all the performance indicators

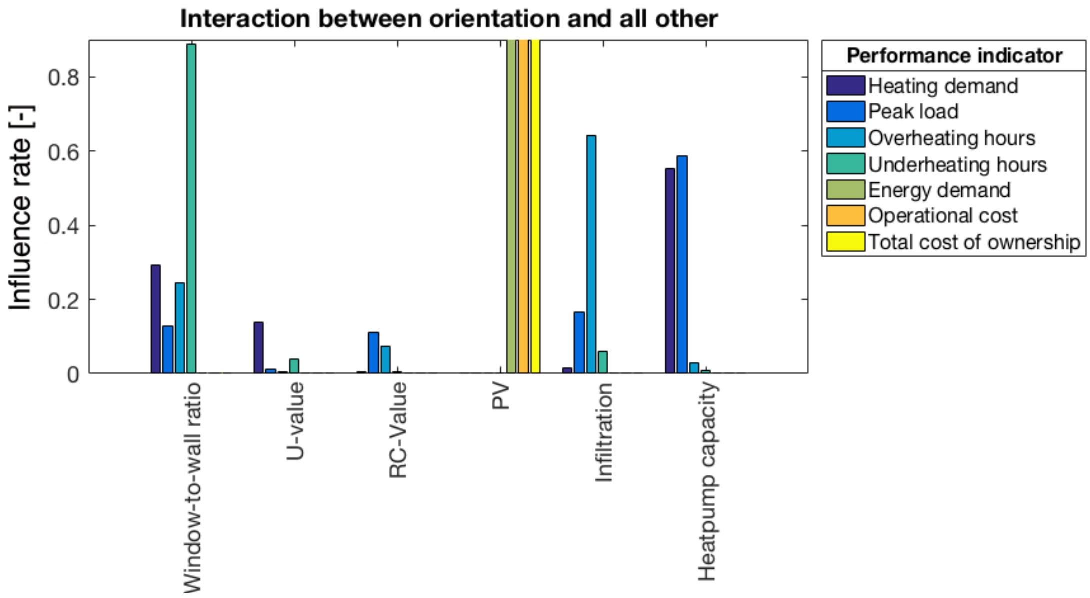


Figure F1-3 Interaction between the orientation and all other parameters over all the performance indicators

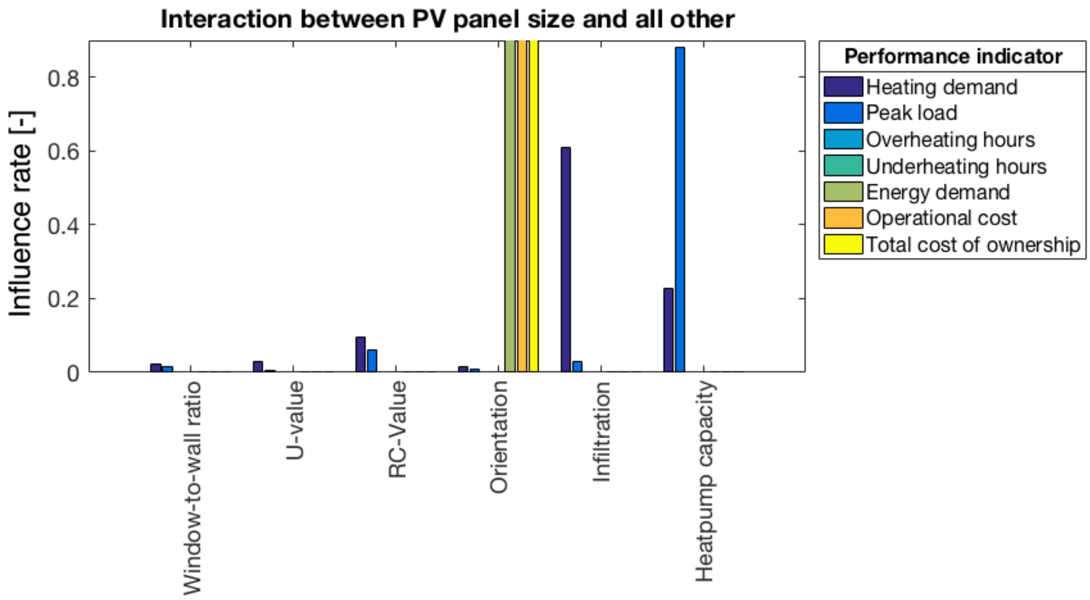


Figure F1-4 Interaction between the PV panel size and all other parameters over all the performance indicators

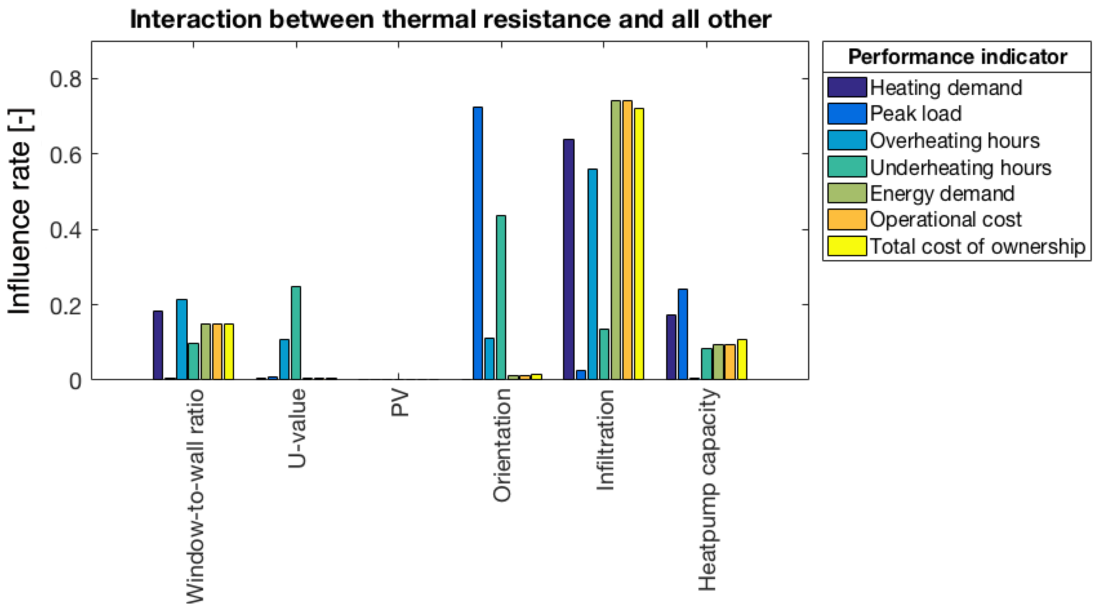


Figure F1-5 Interaction between the thermal resistance and all other parameters over all the performance indicators

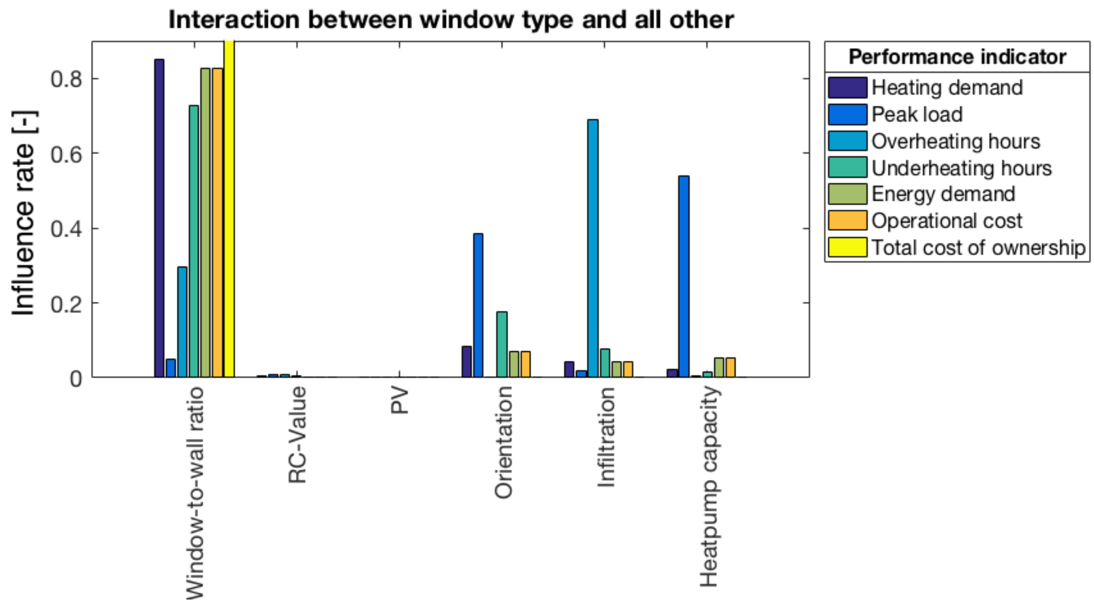


Figure F1-6 Interaction between window type and all other parameters over all the performance indicators

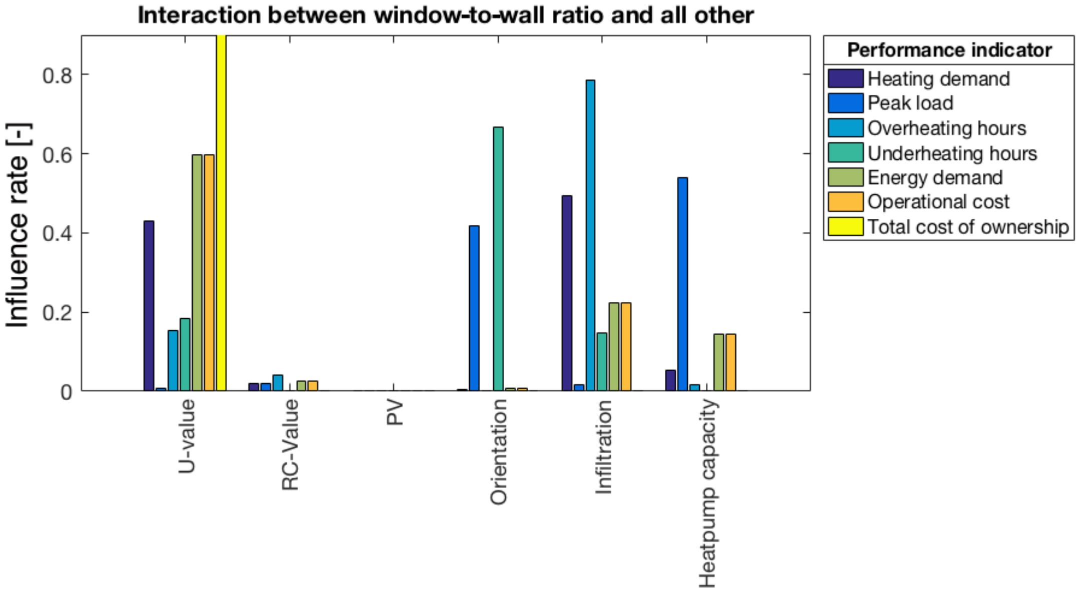


Figure F1-7 Interaction between the window-to-wall ratio and all other parameters over all the performance indicators

Appendix F2

Operational scenarios

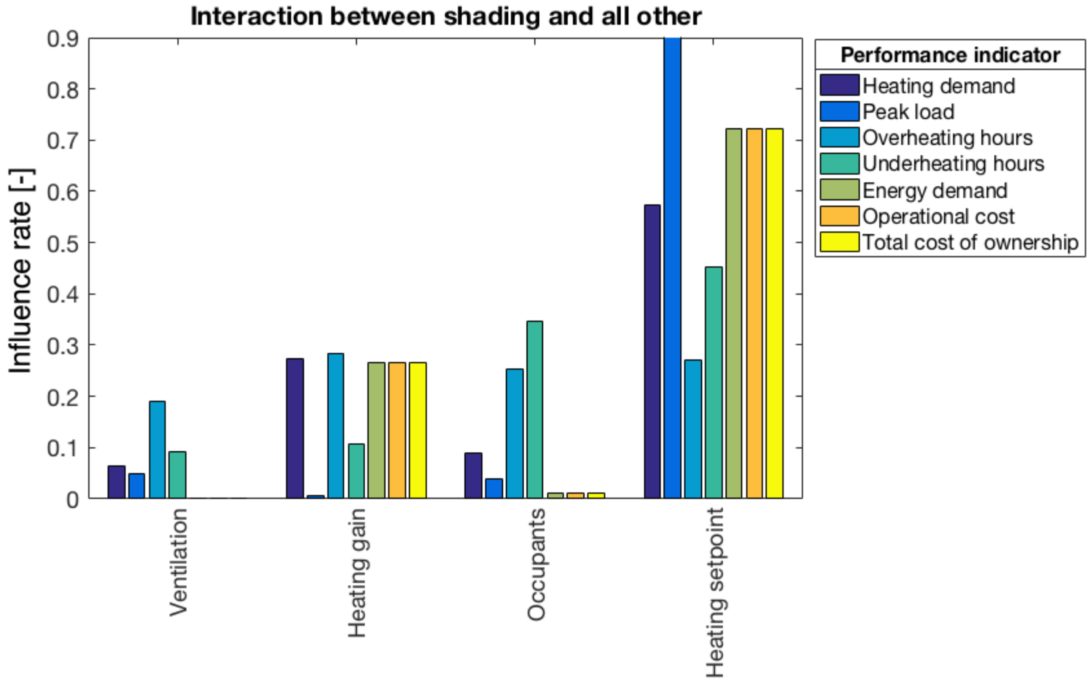


Figure F2-*1 Interaction between shading and all other parameters over all the performance indicators*

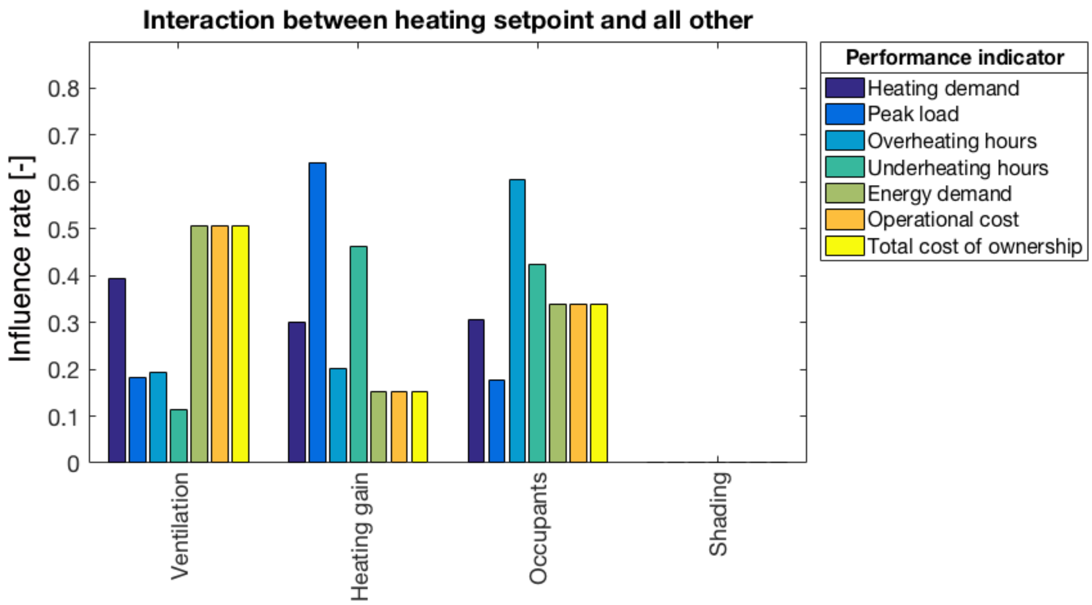


Figure F2-*2 Interaction between the heating set-point and all other parameters over all the performance indicators*

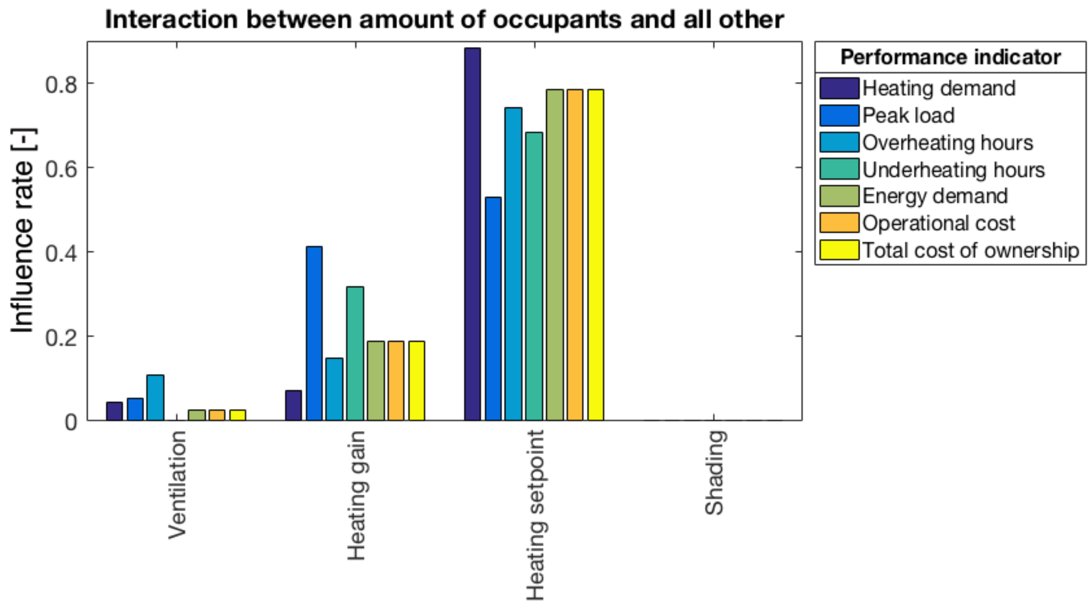


Figure F2-*3 Interaction between the number of occupants and all other parameters over all the performance indicators*

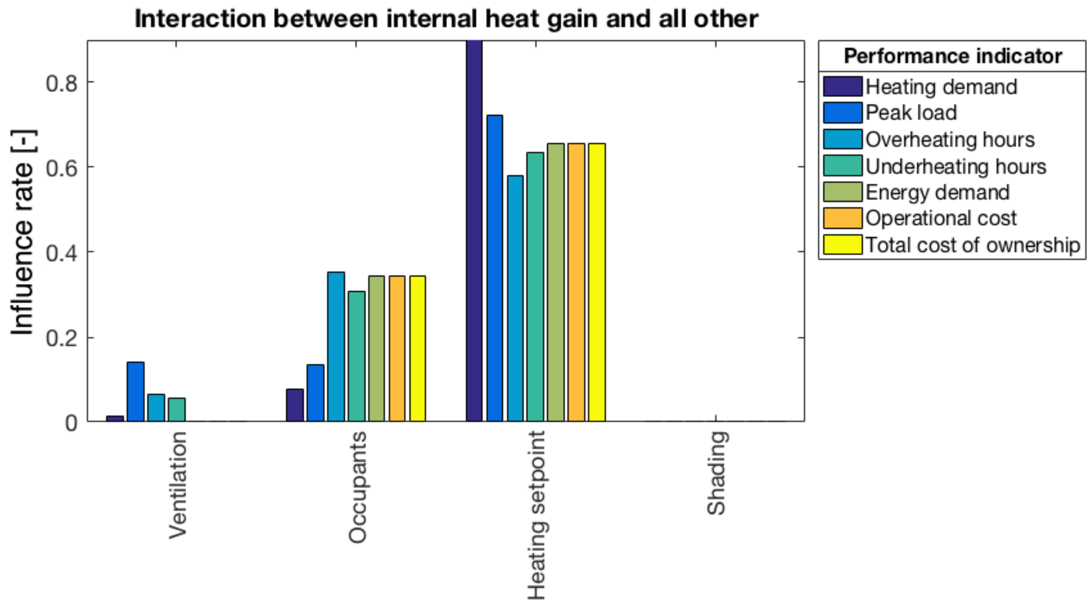


Figure F2-*4 Interaction between the internal heating gain and all other parameters over all the performance indicators*

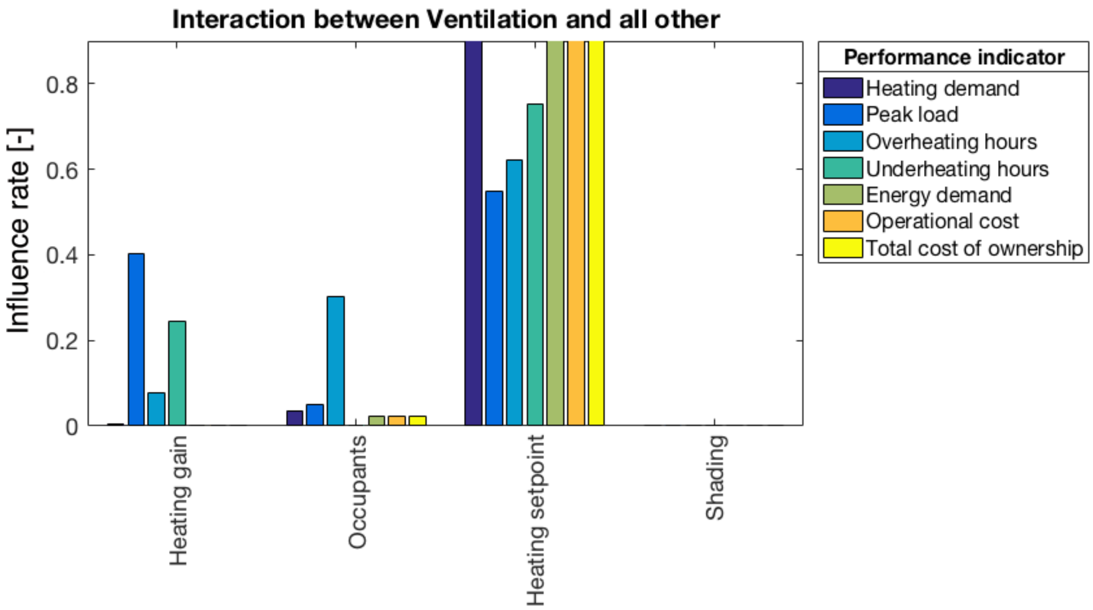


Figure F2-*5 Interaction between the ventilation and all other parameters over all the performance indicators*

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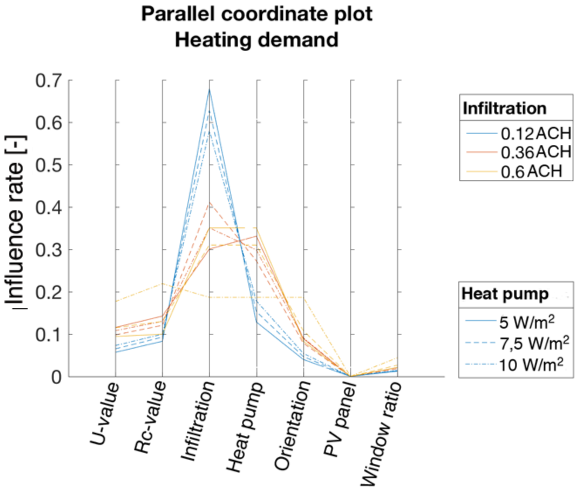
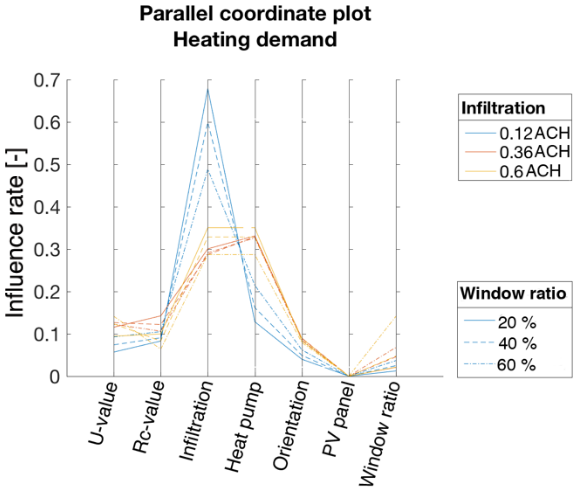
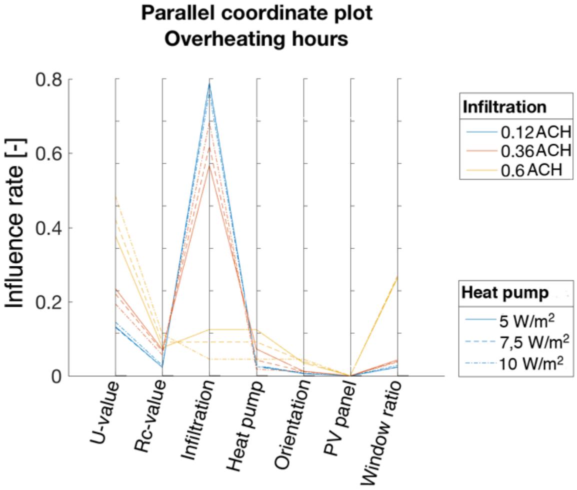
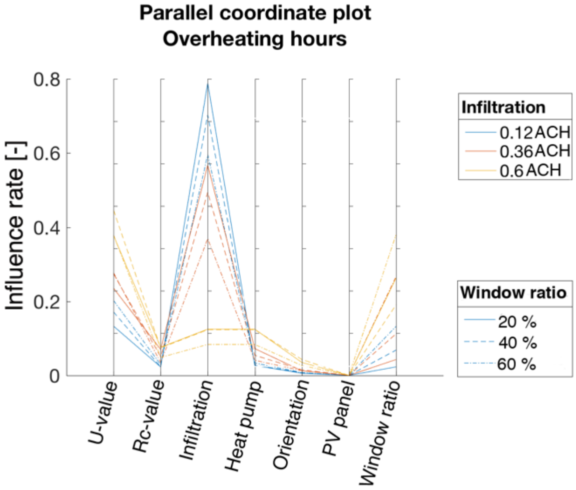
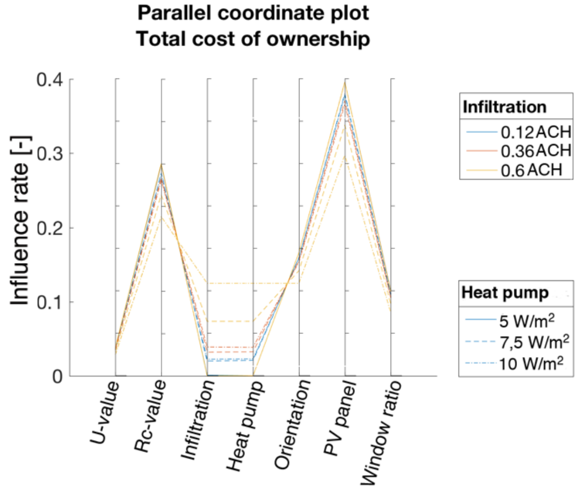
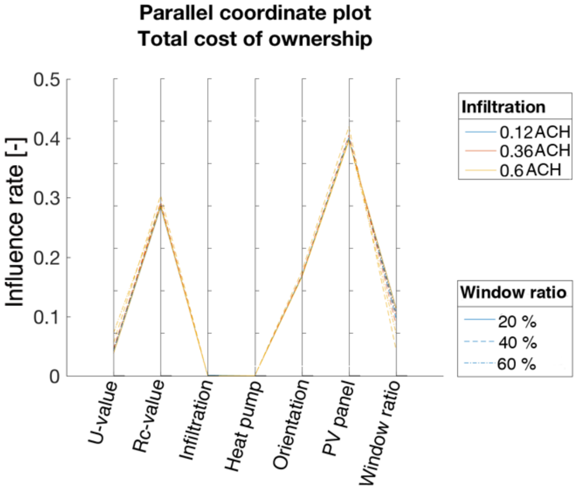

Parallel coordinate plot
Heating demand
Influence rate [-]
U-value
Rc-value
Infiltration
Heat pump
Orientation
PV panel
Window ratio
Infiltration
0.12ACH
0.36ACH
0.6ACH
Heat pump
5 W/m2
7,5 W/m2
10 W/m2

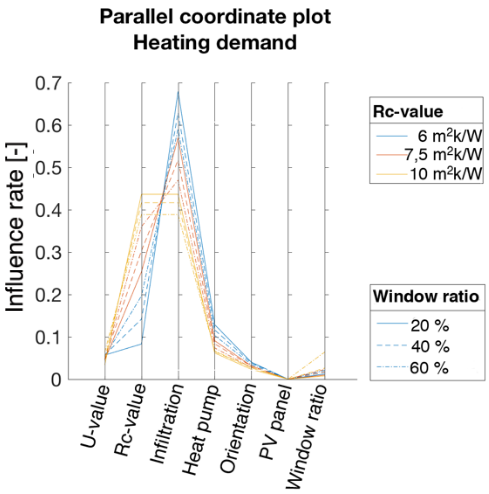

Parallel coordinate plot
Heating demand
Influence rate [-]
U-value
Rc-value
Infiltration
Heat pump
Orientation
PV panel
Window ratio
Infiltration
0.12ACH
0.36ACH
0.6ACH
Window ratio
20 %
40 %
60 %

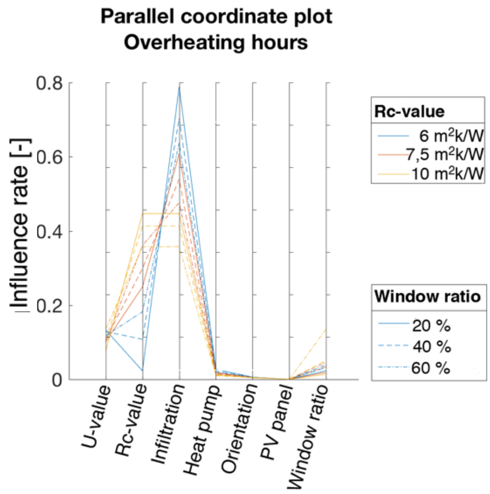

Parallel coordinate plot
Overheating hours
Influence rate [-]
U-value
Rc-value
Infiltration
Heat pump
Orientation
PV panel
Window ratio
Infiltration
0.12ACH
0.36ACH
0.6ACH
Heat pump
5 W/m2
7,5 W/m2
10 W/m2

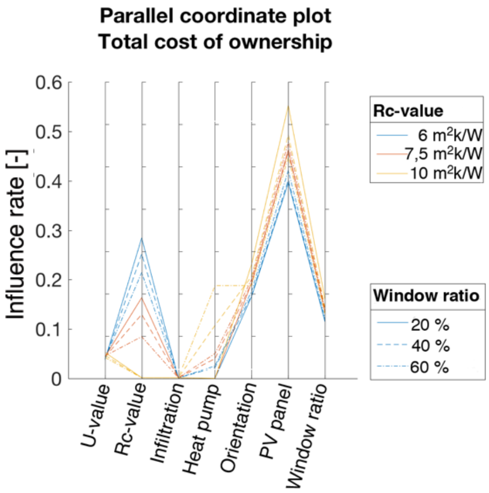

Parallel coordinate plot
Overheating hours
Influence rate [-]
U-value
Rc-value
Infiltration
Heat pump
Orientation
PV panel
Window ratio
Infiltration
0.12ACH
0.36ACH
0.6ACH
Window ratio
20 %
40 %
60 %

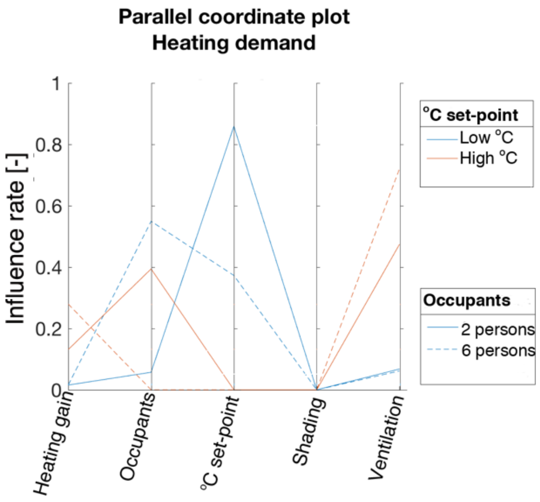

Parallel coordinate plot
Total cost of ownership
Influence rate [-]
U-value
Rc-value
Infiltration
Heat pump
Orientation
PV panel
Window ratio
Infiltration
0.12ACH
0.36ACH
0.6ACH
Heat pump
5 W/m2
7,5 W/m2
10 W/m2

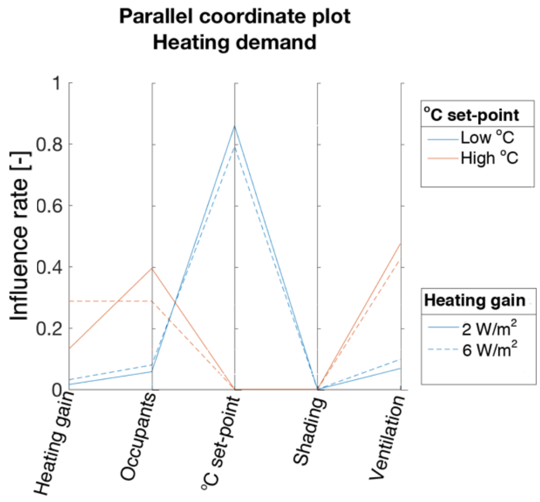

Parallel coordinate plot
Total cost of ownership
Influence rate [-]
U-value
Rc-value
Infiltration
Heat pump
Orientation
PV panel
Window ratio
Infiltration
0.12ACH
0.36ACH
0.6ACH
Window ratio
20 %
40 %
60 %

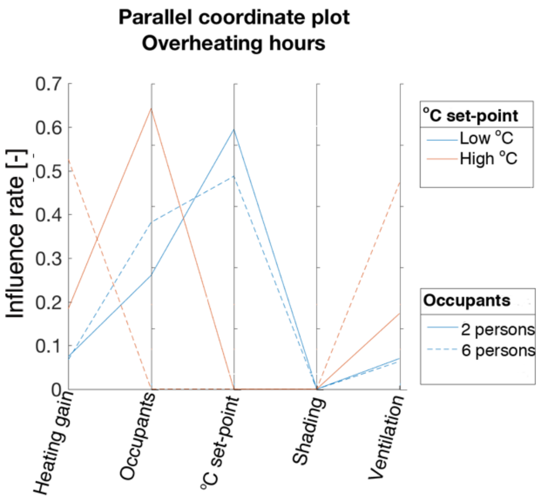

Parallel coordinate plot
Heating demand
Influence rate [-]
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
U-value
Rc-value
Infiltration
Heat pump
Orientation
PV panel
Window ratio
Rc-value
6 m²k/W
7,5 m²k/W
10 m²k/W
Window ratio
20 %
40 %
60 %

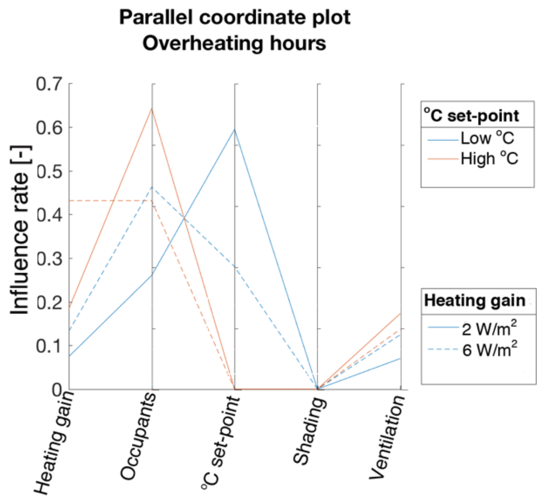

Parallel coordinate plot
Overheating hours
Influence rate [-]
0.8
0.6
0.4
0.2
0
U-value
Rc-value
Infiltration
Heat pump
Orientation
PV panel
Window ratio
Rc-value
6 m²k/W
7,5 m²k/W
10 m²k/W
Window ratio
20 %
40 %
60 %

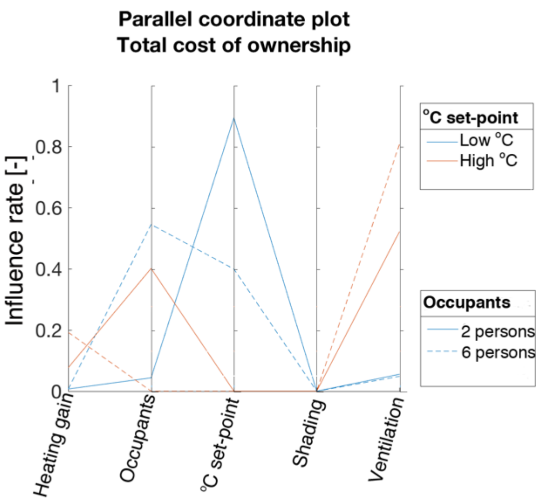

Parallel coordinate plot
Total cost of ownership
Influence rate [-]
0.6
0.5
0.4
0.3
0.2
0.1
0
U-value
Rc-value
Infiltration
Heat pump
Orientation
PV panel
Window ratio
Rc-value
6 m²k/W
7,5 m²k/W
10 m²k/W
Window ratio
20 %
40 %
60 %

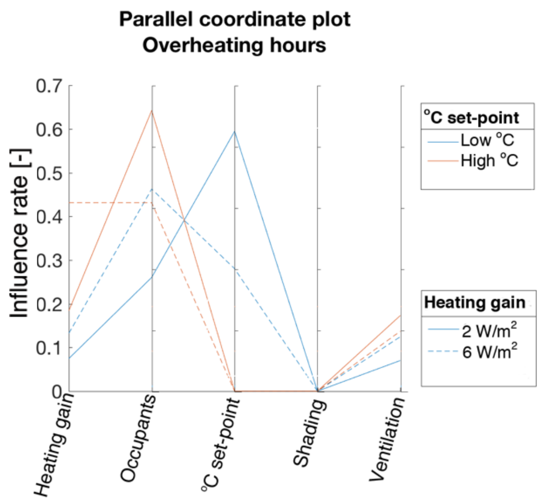

Parallel coordinate plot
Heating demand
Influence rate [-]
1
0.8
0.6
0.4
0.2
0
Heating gain
Occupants
°C set-point
Shading
Ventilation
°C set-point
Low °C
High °C
Occupants
2 persons
6 persons


Parallel coordinate plot
Heating demand
Influence rate [-]
1
0.8
0.6
0.4
0.2
0
Heating gain
Occupants
°C set-point
Shading
Ventilation
°C set-point
Low °C
High °C
Heating gain
2 W/m2
6 W/m2


Parallel coordinate plot
Overheating hours
Influence rate [-]
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
Heating gain
Occupants
°C set-point
Shading
Ventilation
°C set-point
Low °C
High °C
Occupants
2 persons
6 persons


Parallel coordinate plot
Overheating hours
Influence rate [-]
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
Heating gain
Occupants
°C set-point
Shading
Ventilation
°C set-point
Low °C
High °C
Heating gain
2 W/m2
6 W/m2


Parallel coordinate plot
Total cost of ownership
Influence rate [-]
1
0.8
0.6
0.4
0.2
0
Heating gain
Occupants
°C set-point
Shading
Ventilation
°C set-point
Low °C
High °C
Occupants
2 persons
6 persons


Parallel coordinate plot
Overheating hours
Influence rate [-]
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
Heating gain
Occupants
°C set-point
Shading
Ventilation
°C set-point
Low °C
High °C
Heating gain
2 W/m2
6 W/m2

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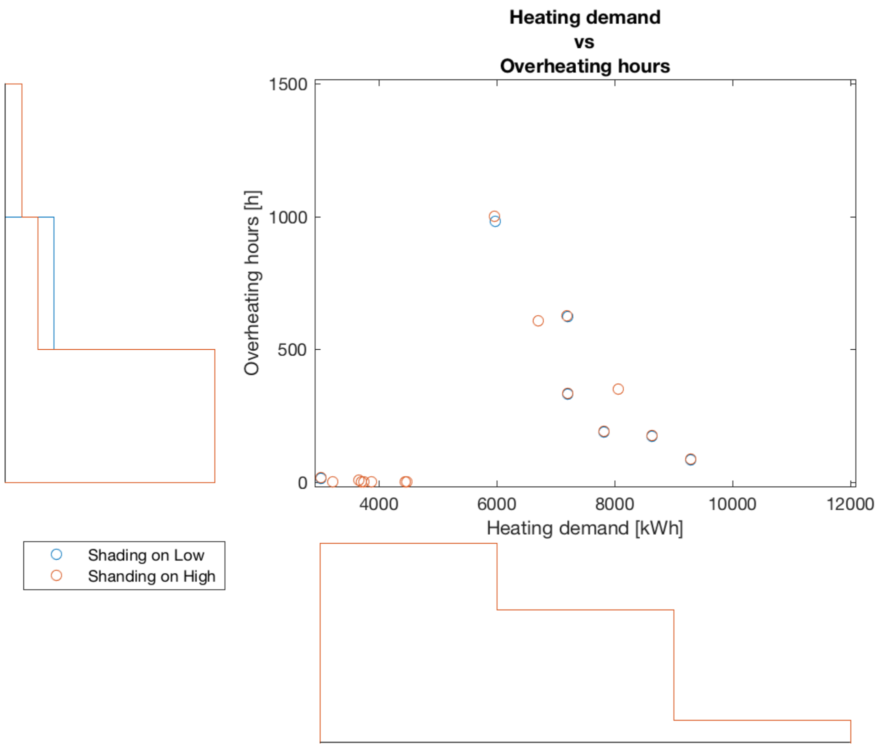

Figure H-1 Scatterplot with corresponding histograms of the Overheating hours and the heating demand where the shading is grouped

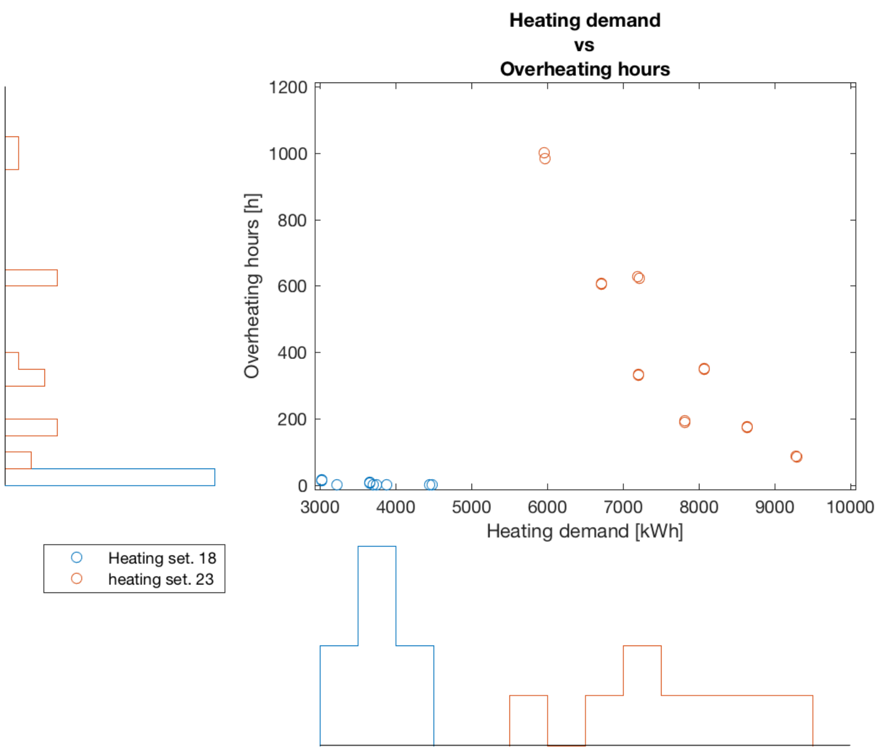

Figure H-2 Scatterplot with corresponding histograms of the Overheating hours and the heating demand where the heating set-point is grouped

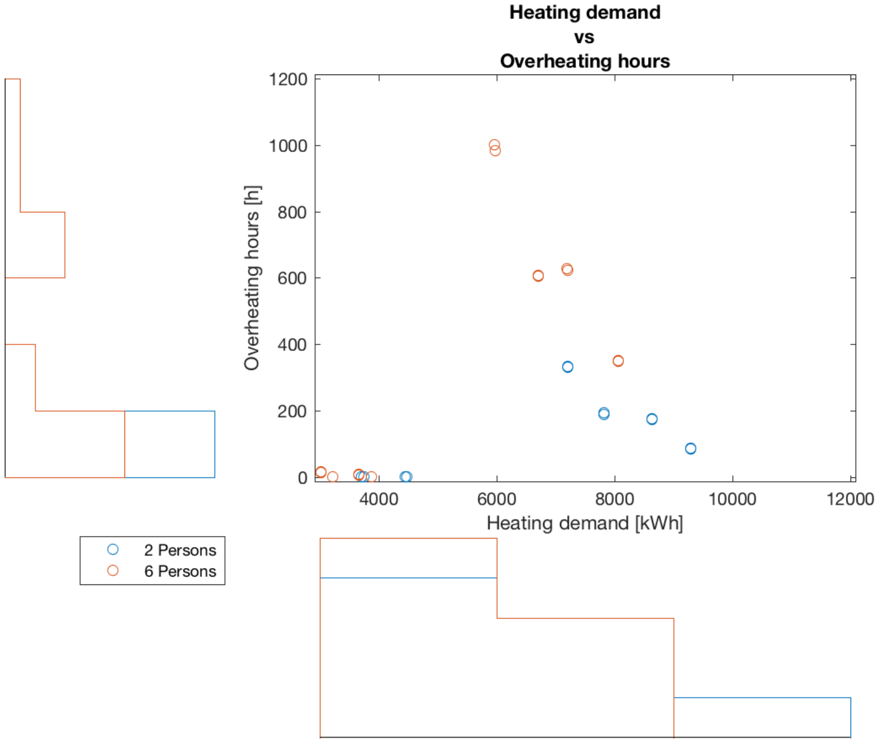

Figure H-3 Scatterplot with corresponding histograms of the Overheating hours and the heating demand where the number of occupants is grouped

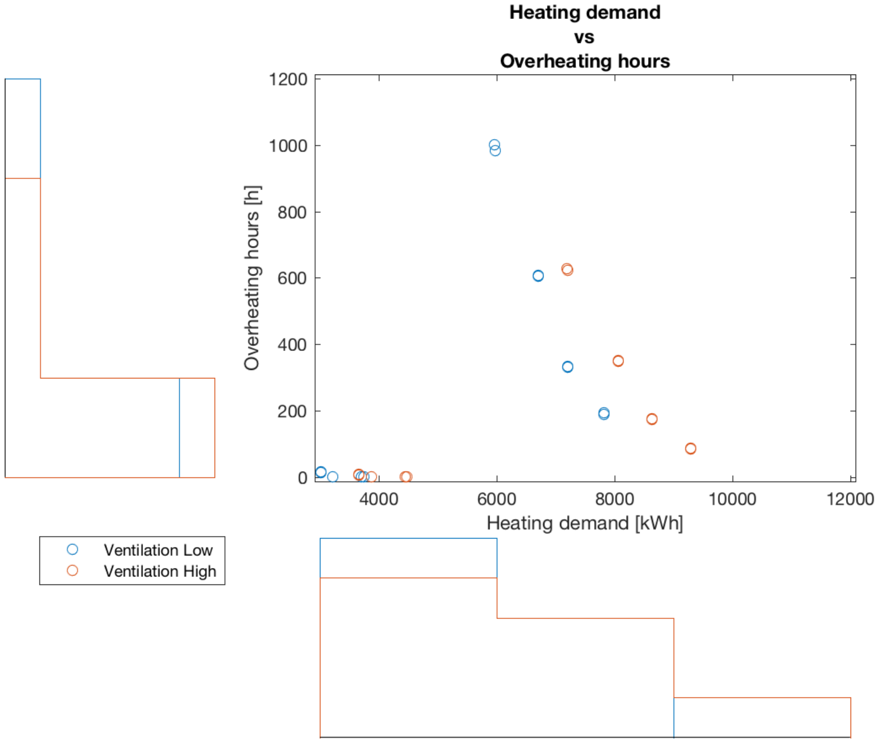

Figure H-4 Scatterplot with corresponding histograms of the Overheating hours and the heating demand where the ventilation is grouped

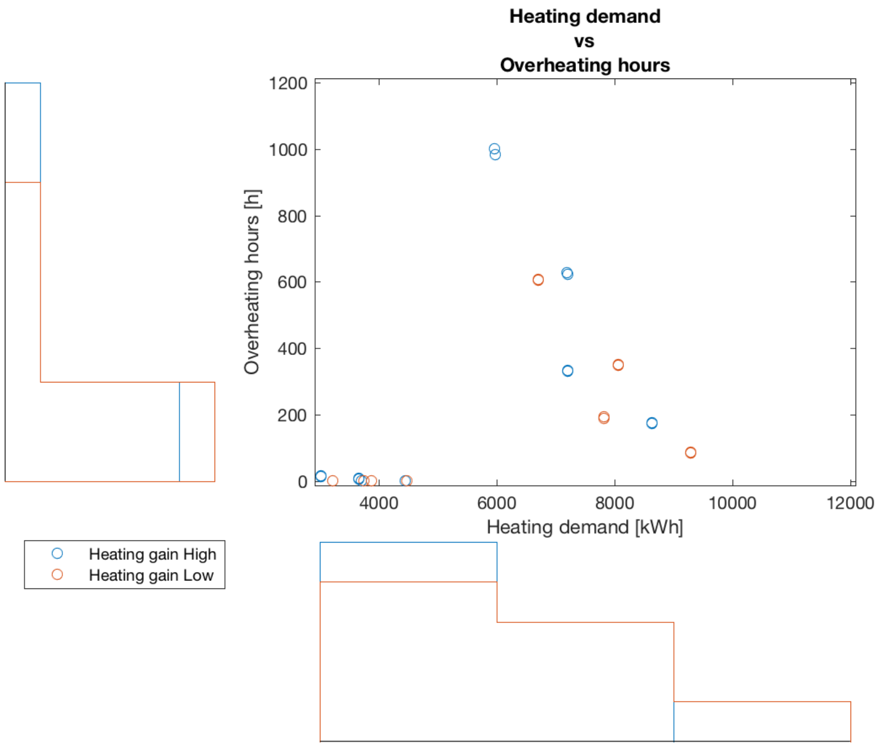

Figure H-5 Scatterplot with corresponding histograms of the Overheating hours and the heating demand where the internal heating gain is grouped

The visualisation tool

A detailed guide how to use the visualisation tool

Table of Contents

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Introduction

The purpose of the visualisation tool, presented in this guide, is to inform stakeholders which parameter(s) (design parameters and operational scenarios) has the most influence on a specific performance indicator. Also, the interaction between different parameters is visualised as well as the interaction between multiple performance indicators.
The goal of this report is to inform the stakeholder how to use the tool, the expectations of the outcomes and how to read the different graphs used in this tool.

Used methods

To tool is split into three separate parts. Part one visualises the most influential parameter on a performance indicator. Part two visualises the interaction between two parameters based on a performance indicator and the most influential combination of two parameters. The last part shows the interaction between multiple performance indicators and shows as well the direction of the influence of the different parameters.
To determine the influences of the parameters the variance-based sensitivity analysis is used in this tool. The choice for this sensitivity analysis is that the variance-based sensitivity analysis can attribute the variance of a model output to each parameter, it can show the interaction on the sensitivity between the parameters and it can take the scale and shape of the input parameters into account. All these requirements are needed to calculate the most influential parameter over multiple independent parameters.

The process

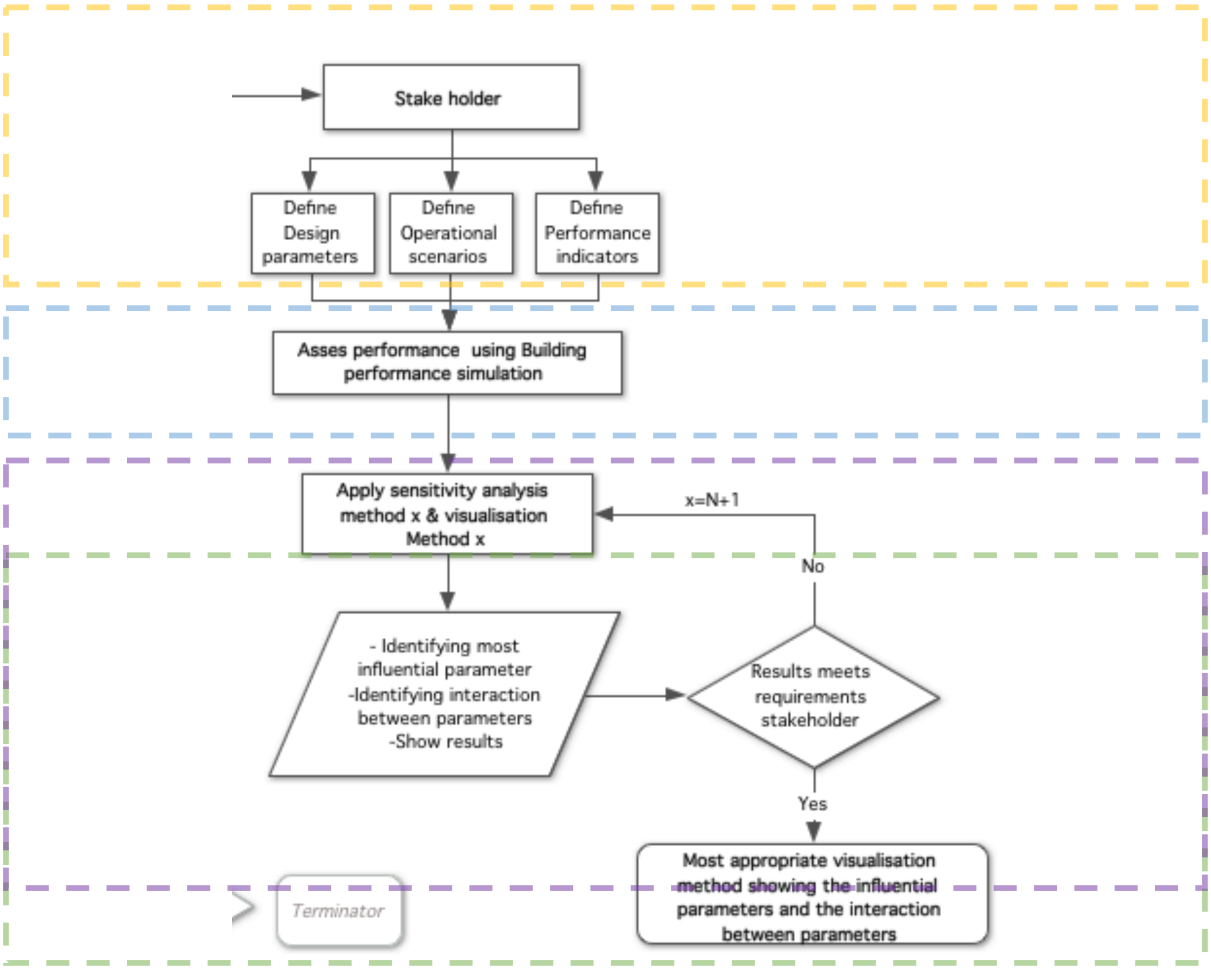

Figure 1 Flowchart of the process of finding the most appropriate visualisation methods showing the influential parameters and the interaction between parameters

Figure 1 shows the flowchart of the process of finding the most appropriate visualisation methods showing the influential parameters and the interaction between parameters. In the coloured boxes, each step is defined in the process. The process starts with the stakeholder and is indicated in yellow in figure 1. The stakeholder defines the most important performance indicators where he is interested

in and based on these performance indicators design parameters and operational scenarios are defined. Also, the minimum and maximum value of each parameter is defined as well as the number of steps taken for each parameter. The stakeholder provides a reference building, or the project building, which will be modelled with a building performance simulation tool.
In blue in figure 1, the simulation of the building is indicated. Based on the requirements of the stakeholder, like the different parameters and their values, different simulations are made based on the design of experiment approach. Here one value changes for each simulation. The outcome of all simulations will be the base for the next step what is applying the sensitivity analysis and the visualisation schemes indicated in green and purple in figure 1. At last, the outcomes of the sensitivity analysis will be shown in the tool to inform the stakeholder in an interactive way of the influences of the different parameters on different performance indicators.

The sensitivity analysis and visualisations schemes.

For this tool, the used sensitivity analysis is the variance-based sensitivity analysis. The advantage of this method is: it can attribute the variance of a model output to each parameter, it can show the interaction on the sensitivity between the parameters and it can take the scale and shape of the input parameters into account.
Because of the many different input variables and the different scales for these input variables of the project, the variance-based sensitivity analysis has the most potential of investigating the influence and interactions of the different parameters. The variance used in this method measures the size of the different values as can be seen in figure 1. Where, if u use the screening based sensitivity analysis which is based on the mean of the values, the mean tries to determine the centre of all the values. Because we are not interested in the lowest, or the highest value for a parameter, but more to the interaction of the parameter, the variance has more benefit.

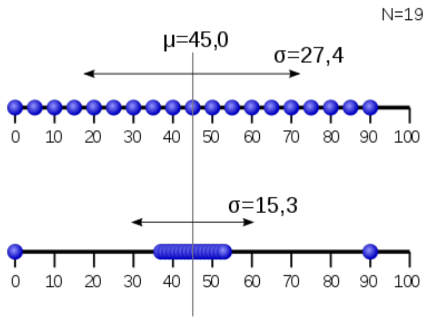

Figure 1 Difference between the mean and variance

The most influential parameter is determined by calculating the percentage of the variance for each chosen parameter. To determine the influence of each parameter the Pooled variance has been used which calculates the variance of the difference. The variance of a parameter is calculated over all outputs. Here all outputs of the investigated parameters are pooled for the different input values of this parameter where the remaining parameters have fixed values. At the end, over all the pooled variances the variance can be calculated for the parameter. The most influential parameter is determined by taking the percentage of all variances of the different parameters.
The results are shown in a parallel coordinate plot. In this plot, the highest peak values indicate the most influential parameter. In this plot, the interaction of two parameters can be shown on the most influential parameter. Here the different values of the two parameters are taken separately and based on only that value the most influential parameter is calculated. Based on this information, the stakeholder can see what the impact is of changing the value of a parameter on the most influential parameter.

For the interaction between different parameters the pooled variance has been used again. Here one parameter (k) is pooled where then the variance is calculated over all the variances of the different input values of one parameter(i). Over these variances, the percentage is calculated to determine the interaction between parameter k and i. The outcome is given in a bar plot which shows the interaction of k and all other parameters. The height of the bars identifies which parameter has the most interaction with parameter k. Note; as can be read, the interaction between the parameters is calculated over K and all other parameters. Therefore, the influence is only given for that parameter and all other parameters. This means, the interaction shown between k and all others can have less influence than, for instance, I and all other, even when the influence rate is higher in k and all other parameters.

To give a more insight of the interaction, the most influential combination between the two parameters, as described above, can be calculated. Here the variance is calculated for one input value of a parameter(i_x) with one input value of another parameter (j_x). For these variances, the percentage is calculated to determine the most influential combination between i and j. The outcome is given in a bar plot. The most influential combination is in this case defined by the height of the bars. This means that the highest bar has the most influence on the performance indicator. Also, can be seen what the influence is when changing the value of a specific value.

At last, the direction of the influence is determined based on the simulation values. Here all the values are plotted in a scatterplot based on two performance indicators which are grouped by one parameter. Based on this graph it is possible to identify the direction of the parameter on two performance indicators.

Use of the visualisation tool

The purpose of the visualisation tool is to inform the stakeholder, in an interactive way, which parameter has the most influence on the performance indicator, and to show the stakeholder which parameters have high interactions between each other.

The tool is divided into three tabs [figure 2].

- Tab 1: Most influential parameter
- Tab 2: Interaction between parameters & most influential combination between parameters
- Tab 3: Interaction of one parameter on two performance indicators.

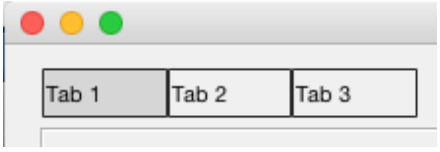

Figure 2: The tool is divided into three tabs.

Tab 1: Most influential parameter

The most influential parameter is visualised in a parallel coordinate plot as shown in figure 3. Here all parameters are set out to the influence rate [%] on a scale of 0-1 and the different parameters based on the design parameters or operational scenarios.

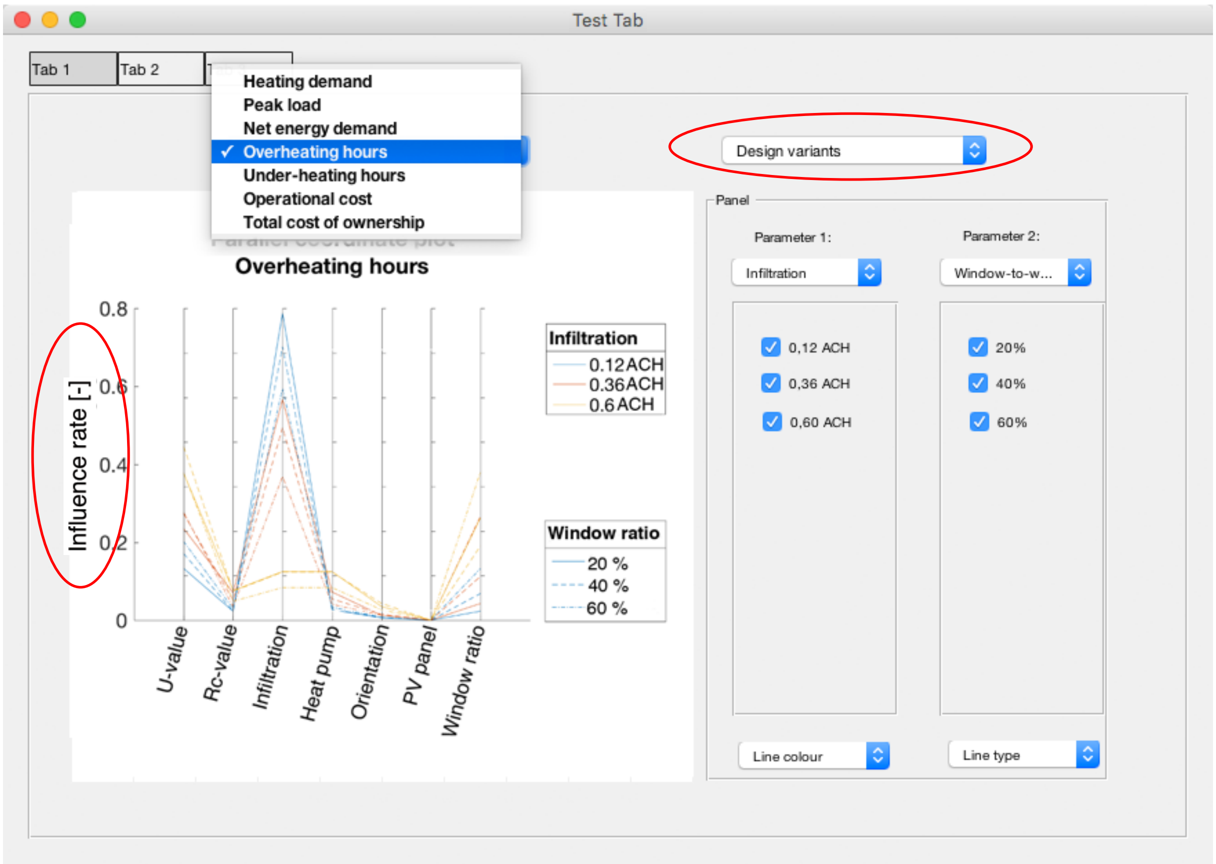

Figure 3: total overview of tab 1 showing the parallel coordinate plot which shows the most influential parameter.

The first step is to select the performance indicator followed by the design parameters or operational scenarios [figure 4]. The parallel coordinate plot will show the most influential parameter of the selected performance indicator. The selected parameter group will show the most influential parameter of this group.

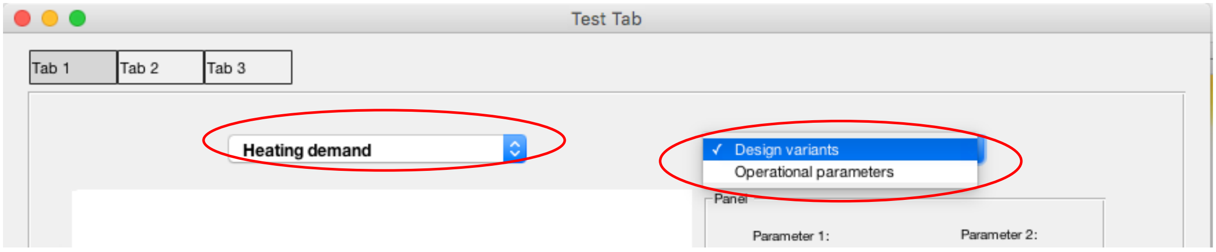

Figure 4: location of selecting the heating demand and the design parameters or operational scenarios

The next step is to select two parameters and the interesting values.
The parallel coordinate plot will show the lines corresponding to the selected values. Also, it is possible to determine which parameter is visualised in colours and which parameter is visualised in different line types.
With these selections, it is possible to investigate the influence of two parameters on the most influential parameter of the selected performance indicator. By selecting each value one by one, the increase of decrease of the most influential parameter can be seen.
an example is given in figure 6. This example is from a previous model; however, the principles are the same. In this example, a parallel coordinate plot is shown where the thermal resistance and the thermal mass are compared. In this example, the line colour indicates the thermal mass and the line type indicates the thermal resistance. The blue lines and the solid lines indicate low values, where the orange lines and the dotted lines indicate high values. as can be seen in the example the influence is high for the thermal resistance, however, when the thermal resistance and the thermal mass increases the influence of the thermal resistance on the performance indicator decreases. Where the influence of the thermal mass increases.

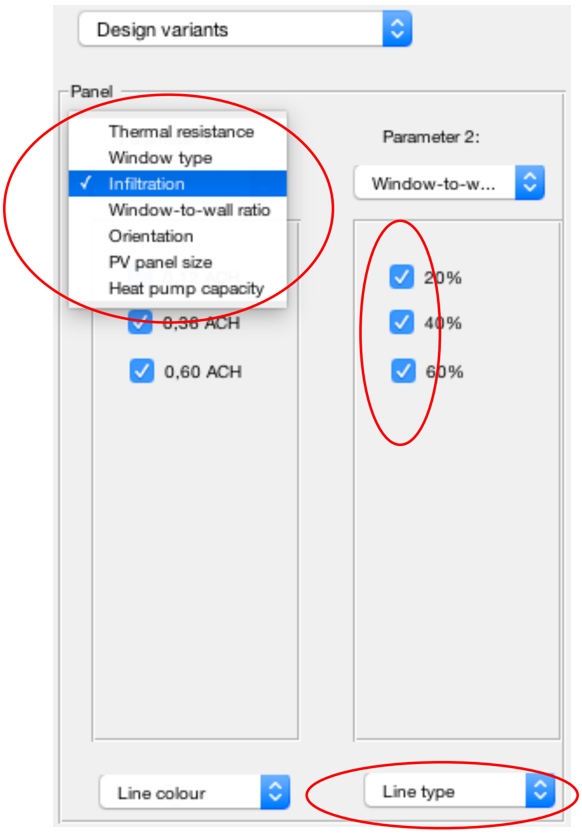

Figure 5: selecting the interested parameters and corresponding values

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By changing the values of the parameters in the current situation, and changing as well the different parameters the influence on the performance indicator can be investigated.
At last, it is possible to switch the line colours, and line types per parameter. This to give the possibility for the stakeholder to switch to enhance the visualisation to its own benefits.

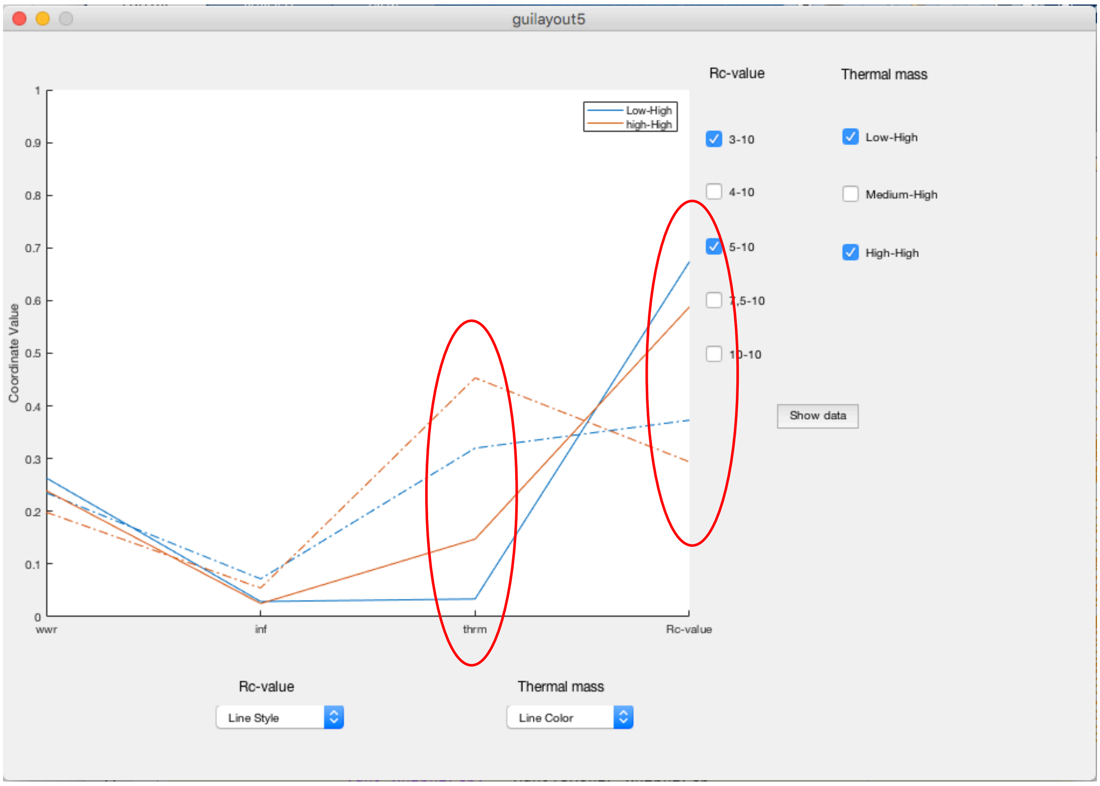


Figure 6: Example of a previous model where the change is visible of the most influential parameter. When the thermal resistance and thermal mass increases decrease the thermal resistance as the most influential parameter where the thermal mass increases as the most influential parameter on the performance indicator.

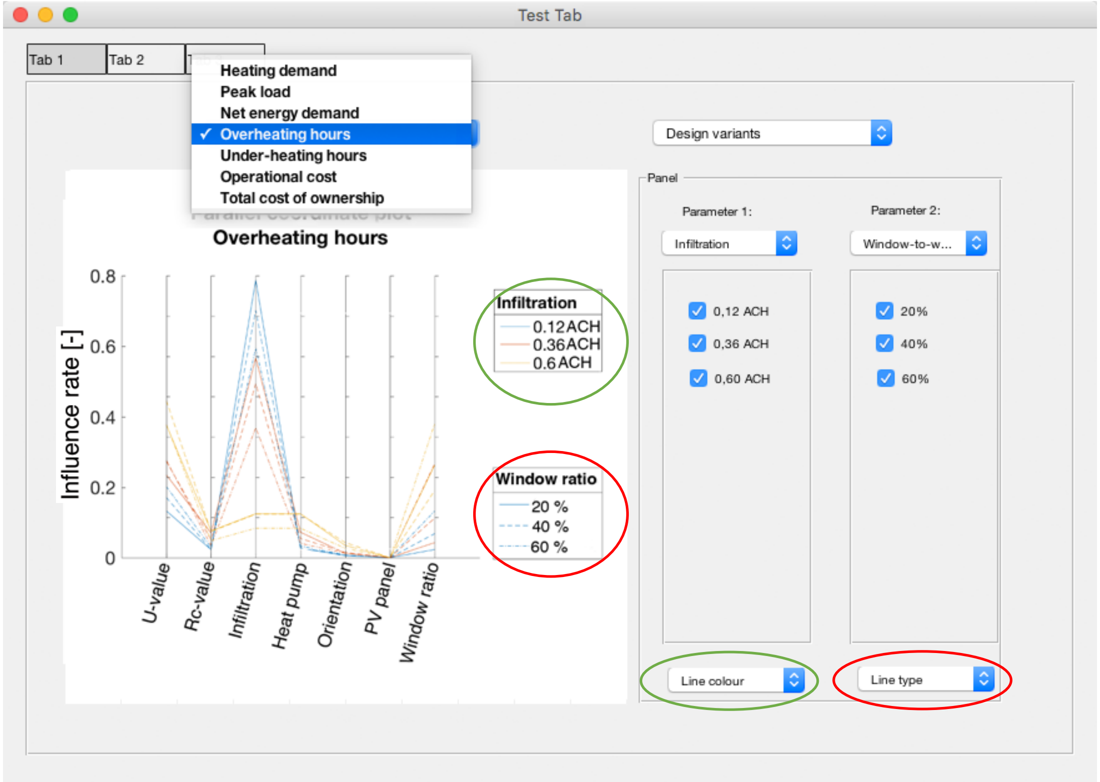


Figure 7: The two types of line visualisation. In green the line colours and in red the line types

Tab 2: Interaction between parameters & most influential combination between parameters

The interaction between parameters and the most influential combination between parameters are shown in bar plots as shown in figure 8. The interaction between parameters is shown in the upper part of the tool, where the most influential combination is shown in the lower part of the tool.

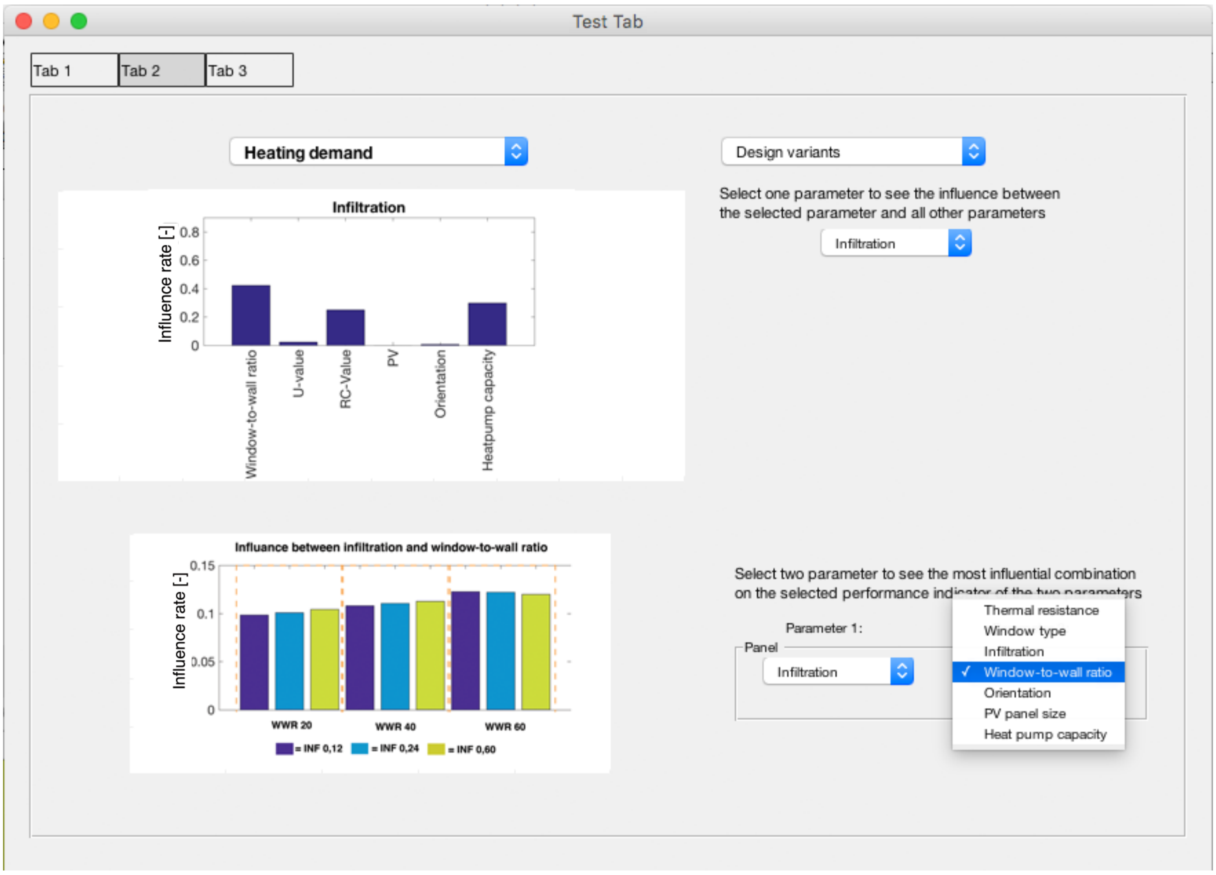


Figure 8: Total overview of the second tab in the tool within the upper part the visualisation of the interaction between parameters, and in the lower part the most influential combinations of two parameters.

The first step is the same as in the first tab, and that is defining the performance indicator and choosing between the design parameters or the operational scenarios as shown in figure 4.

The second step is selecting one parameter where then the interaction is shown between the selected parameter and all other parameters [figure 9]. The results are shown in a bar plot. The height of the bar plot indicates the strength of the interaction between the selected parameter. As already mentioned, a comparison between different parameters is, until now, not possible. The results of one bar plot show only the interaction between the selected parameter and all others. An example of this can be found in figure 10. The influence rate between the infiltration and the RC-value in figure 10a shows a value around 0.3 where the influence rate between the RC-value and the infiltration in figure 10b shows an

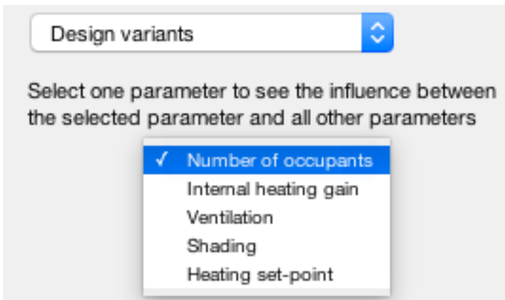
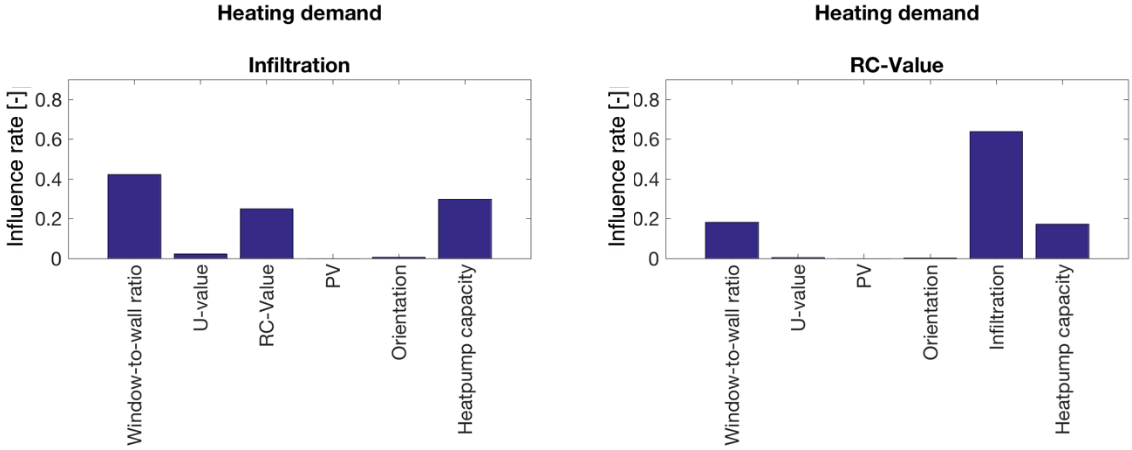


Figure 9: Selection of the parameter to investigate the interaction between the selected parameter and all other

interaction around 0.6. Although the interactions between these two parameters are the same, the values are different. Based on these two graphs we can see that the interaction between the infiltration and the window-to-wall ratio and the infiltration and heat pump capacity is higher than all interactions of the RC-value and all other parameters.



a *b*

Figure 10: interaction between two parameters with a, the infiltration and all other and b, the interaction between the RC-value.

The third step in this tab is selecting two parameters to investigate the most influential combination between these parameters on the performance indicators as shown in figure 11 and 12.

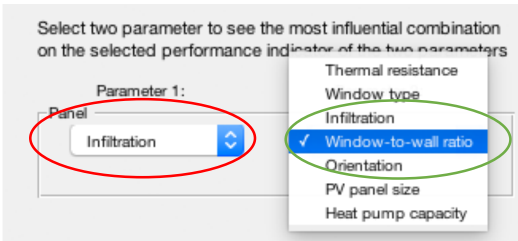


Figure 11: Selection of the two parameters to investigate the most influential combination on a performance indicator

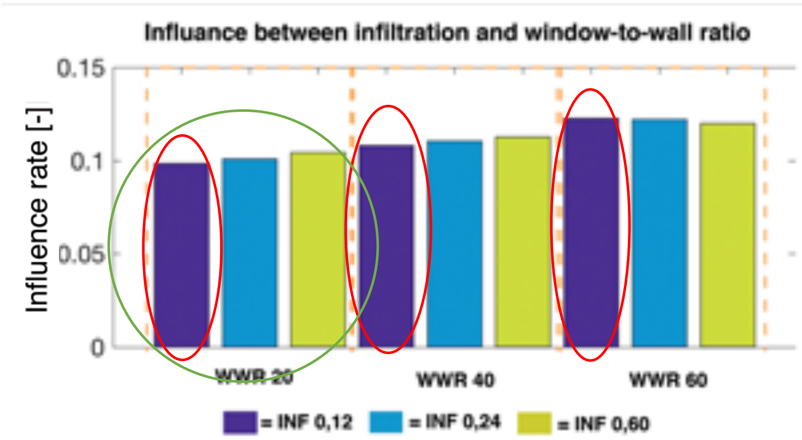


Figure 12: The highest bar indicates the most influential combination between the infiltration and the window-to-wall ratio.

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Here the different values of the first parameter are split over parameter two. This can be seen in figure 11 and 12 where the lowest values of the infiltration are circled by the red circle, and the lowest value of the window-to-wall ratio is circled by the green circle. In this figure, we can see that an increase of the infiltration results in an increase of the influence on the performance indicator, however, when the window-to-wall ratio has a high value, the influence on the performance indicator decrease with respect to the increase of the infiltration.

Tab 3: Interaction of one parameter on two performance indicators

The relation between two performance indicators is visualised in a scatterplot, as shown in figure 13, where one parameter is selected to group the different input values of this selected parameter.
With this figure, the relation between two performance indicators can be investigated based on one parameter. This is as well possible with the parallel coordinate plot in the first tab, however, in this figure the direction of the influence is as well visible. As can be seen in figure 13 here can be seen that a low infiltration results in low heating demand, but for high overheating hours. A high infiltration results in a high heating demand and low overheating hours.

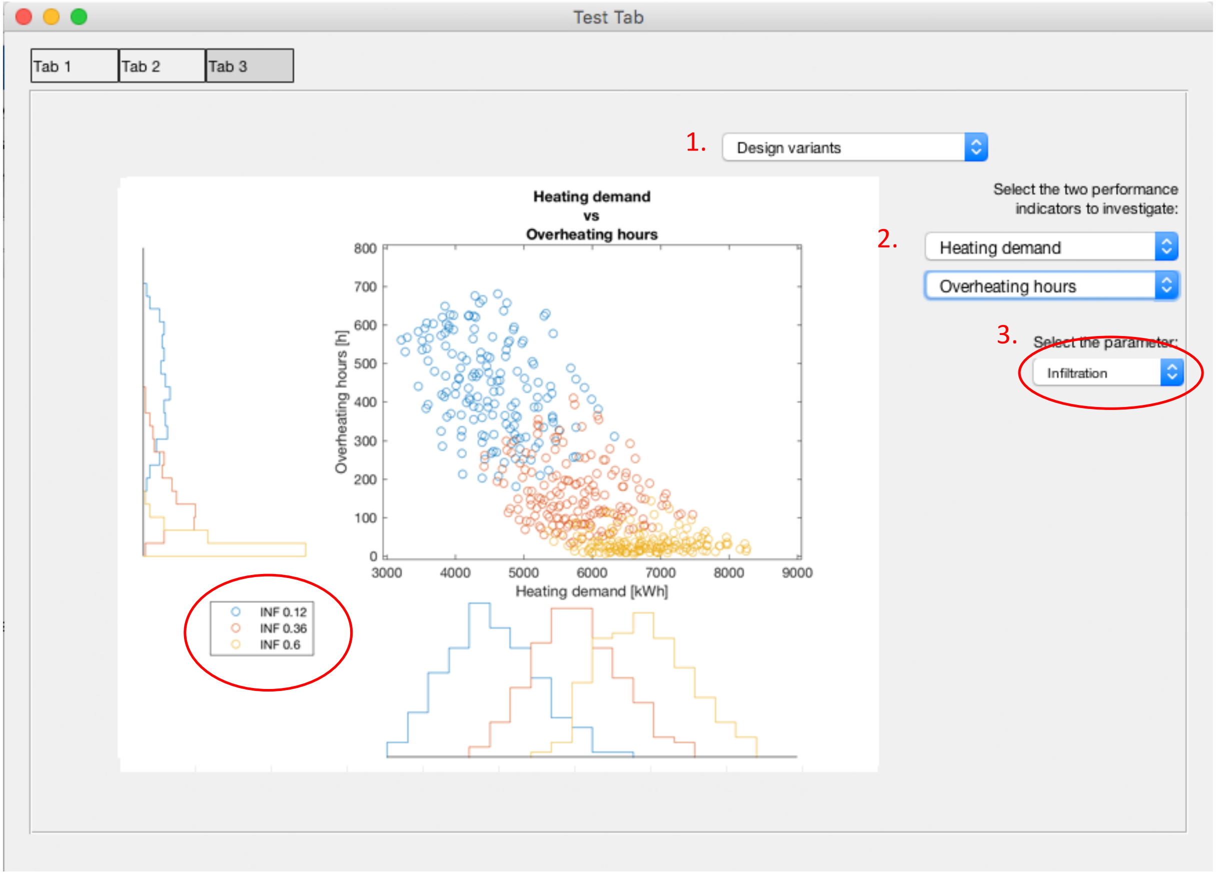

Figure 13: Tab 3 showing the scatterplot with the corresponding histograms where first the design variables or operational scenarios is selected, followed by the performance indicators and at last the parameter.

The first step is selecting the design parameters or the operational scenarios. Followed by the two performance indicators. At last, the parameter is selected to group the different values.
The histograms which are shown in the graphs corresponding to the performance indicators and the different values. based on the histogram the interaction and the direction can be seen as well.

Appendix J

In this appendix, the results of Chapter 5 will be evaluated. At first the sensitivity analysis methods, followed by the building performance simulation. At last the different results are evaluated as well as the different visualisation methods will be evaluated.

The sensitivity analysis methods

As mentioned and investigated in chapter 2, there are several methods to perform sensitivity analysis. For this study, the used sensitivity analysis is the variance-based sensitivity analysis. The advantage of this method is: it can attribute the variance of a model output to each parameter, it can show the interaction on the sensitivity between the parameters and it can take the scale and shape of the input parameters into account.

Because of the many different input variables and the different scales for these input variables of the project, the variance-based sensitivity analysis has the most potential of investigating the influence and interactions of the different parameters. The variance used in this method measures the size of the different values as can be seen in Figure 0.1. Where, if u use the screening based sensitivity analysis, the mean try to determine the centre of all the values. Because we are not interested in the lowest, or the highest value for a parameter, but more to the interaction of the parameter, the variance has more benefit.

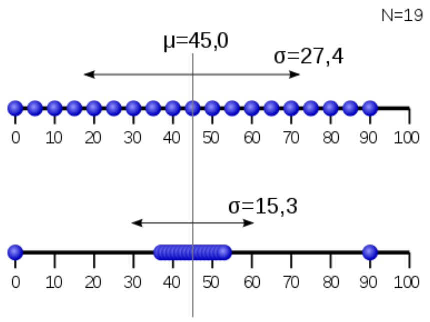

Figure 0.1 Difference between the mean and variance [56]

The results of the used method for determining the most influential parameter shows that it is possible to determine these influences. Not only the boxplot shows the most influential parameter, but as well the bar plots and parallel coordinate plots. Therefore, we can say that the used method can be used to determine the most influential parameter.

The interaction between the different parameters is as well calculated with the variance-based sensitivity analysis. As shown in 6.1.3 of the main report, it is possible to show the interaction between the different parameters. However, In the current situation, a comparison is made between one parameter and the other parameters. This results in an interaction of one parameter with respect to all other parameters. Changing the parameters, the value of the same parameter can be different. Table 1 shows an example of different parameters. Here, the interaction of Parameter i between the other parameters gives an influence rate [%] over all these combinations. Where parameter j gives an influence rate [%] over parameter j and all other parameters. When the influence of parameter j and i is higher than all other influences of parameter j and the rest i and j will have great influence. However, looking at parameter I and j (what are the same) this can have a low influence comparing with all other parameters and parameter i. this can be solved by taking all possible interactions and take the total variance over all the combinations.

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Because the percentage is calculated over all the combinations the influence rate will be very low for most of the values. Also, some interactions between parameters can be great but can have low influence on the performance indicator because of the influence rate of the parameter itself.
In the situation, as it is now, the stakeholder can see which parameter has the most influence, where he then, based on the most influential parameter, can choose between which parameters he wants to know the interactions.

Table 2 Example of same interaction between parameters but different influence rate.

Comparison 1	Percentage 1	Comparison 2	Percentage 2
Parm I - parm x	…	Parm j - parm x	…
Parm I - parm y	…	Parm j - Parm y	…
Parm I - parm j	…	Parm j - Parm i	…

The building performance simulations

The simulations of the case-study are performed in TRNSYS in combination with Matlab, what is also used for the calculations and the visualisation of the sensitivity analysis. As described in Chapter 3 of the main report, the TRNSYS model is build up from different components. The building design is described in type 56 of TRNSYS where the ventilation, heating system, heat recovery and solar shading are described in different components. As described in 6.1 of the main report, the reference building has a net energy consumption what is average for a Dutch terraced house.
Matlab is used to generate an automatic process of changing each variable one at the time and let TRNSYS simulate the building. To lower the calculation time of this process, the energy generated from the PV panels are calculated separately and add later to the performance indicators. Therefore, there are only 15552 simulations needed. The calculation time of one simulation is roughly 54 seconds, depending on the input values. This results in an overall simulation time of more than 8 days.
Because of the many input variables in TRNSYS and Matlab errors can occur. Looking to the results of all the simulations, two parameters shows inconsistencies with respect to the other parameters. The first parameter is the shading system. The results show, that the shading has little to no influence what so ever on any performance indicator. Comparing the number of hours, the solar shading should be working for two different values for the solar shading in the building case model in TRNSYS, shows that there are differences between the outputs. However, the differences between the low heating gain and the high heating gain are low respectively 281 hours and 299 hours over a full year. Therefore, because of the small difference, the solar gain could have low influence on all other performance indicators with respect to the influence of all other parameters what could result that the shading shows no interaction.
the second anomaly can be found in the heating set-point of the building. the influence of the heating set-point is high, where all other influences are low. This can be explained by a human error in the Matlab script for changing the heating set-point. Due to an error, the lowest heating set-point never changed and remains fixed at a temperature of 14°C. this results, for a low heating set-point of 14°C when there are no occupants in the building and 18°C when there are occupants in the building, and for a high heating set-point of 14°C instead of 18°C when there are no occupants in the building and 23°C when the building is occupied.

Reference building and simulation results

One dimensional sensitivity analysis.

In this section, a discussion is given of the most influential parameters of some performance indicators. Chapter 5 shows the results of the simulations, and of the sensitivity analysis. As described in 5.1 of the main report, the infiltration is the most influential parameter of the heating demand. The influence of the infiltration is high with respect to all other parameters. The thermal resistance (Rc-value and U-value), as well as the window-to-wall ratio, shows some influence although, less than expected. Hoes (2014) has stated that the minimum value for infiltration should be 0.12 ACH where the maximum value of an average household should be 0,36 ACH. Kottiredy (2015) Used as maximum value 0.60 ACH. To compare the most influential parameter, where the infiltration is set to 0.6 ACH and to 0.36 ACH, all values of 0.60 ACH for infiltration are left out. Figure 6.1 shows the reduction of the infiltration as the most influential parameter, where all other increases. However, the infiltration still has a high influence.

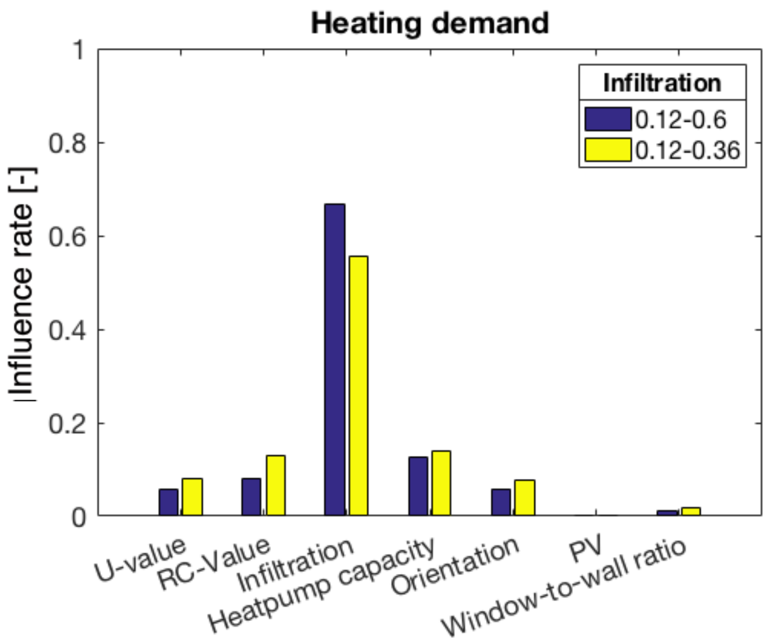

Figure 0.2 Most influential parameter for an infiltration of 0.12-0.6 ACH and 0.12-0.36 ACH

another aspect of the high influence could be the heat losses of the building. To define the heat losses of the building the infiltration is compared with the thermal resistance. Therefore, the following formulas have been used:

$$H_i = c_p \, \rho \, n \, V \, \Delta T \qquad (6.1)$$

$$H_i = U \, A \, \Delta T \qquad (1)$$

where:
H_i= heat loss infiltration
H_t= heat loss wall
c_p= specific heat air
ρ= density of air
U= Overall heat transfer coefficient
n=ventilation rate AHC
A=wall area
V=Volume of the room
ΔT= temperature difference

An infiltration of 0,6 ACH results in a total heat loss of approximately 2000W and an infiltration of 0,12 Ach results in a heat loss of 400W, where a thermal resistance of 6 m^2K/W results in a heat loss of 1035W and a thermal resistance of 10 m^2K/W in 62W. The difference between the heat losses for the infiltration is higher than that of the thermal resistance. This can explain the high influence on the infiltration.

The total cost of ownership has three most influential parameters; PV panel size, Thermal resistance and the window-to-wall ratio. As explained in chapter 4 the total cost of ownership is defined based on the operational cost, the PV panels, insulation material and windows. The PV panels have great influence on the total cost of ownership. Looking to table 4.7 and 4.9 we see that the insulation cost is respectively high, but the difference between the values is lower than between the cost of the PV panels. The choice for the size of the PV panel will not only be depending on the cost but as well on the total net energy demand of the building. Looking to Figure 0.3 we see that the PV panel size has great influence on the energy demand.

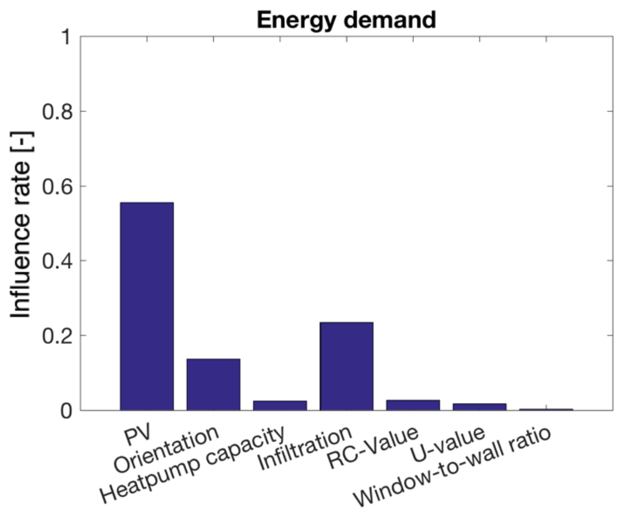

Figure 0.3 Most influential parameter for the net energy demand calculated with the variance-based sensitivity analysis.

Figure 0.4 shows the scatterplot, where the energy demand is set out to the total cost of ownership with the size of the PV panels as chosen parameter. Figure 0.4 shows that, when a PV panel of 30 m^2 is used, the total energy demand is low, but the total cost of ownership is high. Using a small PV panel, we can see that the total cost of ownership is low, but the total energy demand will increase. Based on Figure 0.3 we already concluded that the PV size has great influence on the energy demand. Based on Figure 0.4 we can see that indeed the PV panel size has great influence on the energy demand and as well on the total cost of ownership.

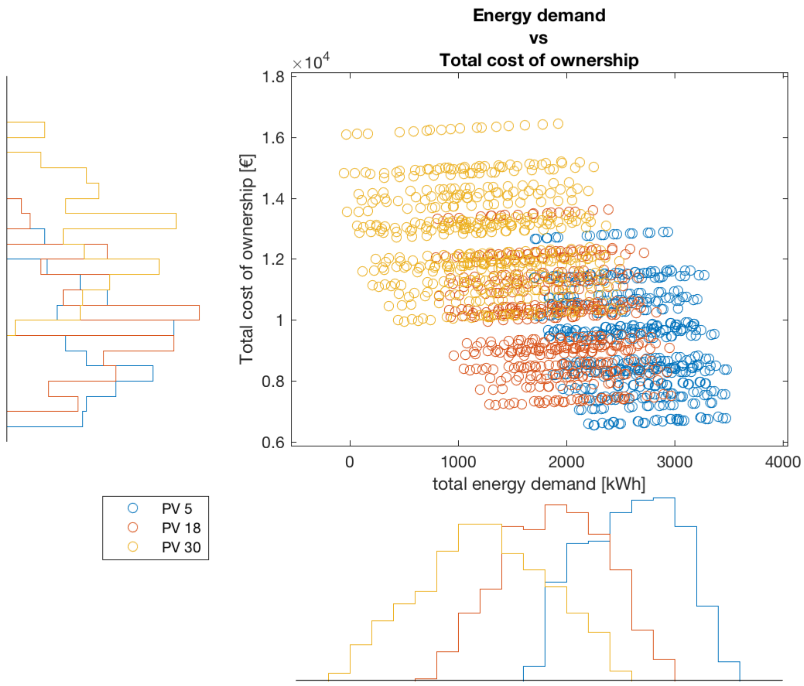

Figure 0.4 Scatterplot with corresponding histograms of the total cost of ownership and the net energy demand where the PV-panel size is grouped. Here the PV panel size has influence on both performance indicators, a low PV panel size results in a high-energy demand, but a low total cost of ownership.

The visualisation methods

For this research, several visualisation methods have been used. The bar plot is used to identify in the beginning the most influential parameters. When investigating the influence of the different values of a parameter the bar plot is converted to a parallel coordinate plot. By using the parallel coordinate plot several observations can be shown in one graph. In the current situation, the line colours can be changed, and the line types to indicate the parameter where the line belongs.

After discussing the results, a possible alternative for the parallel coordinate plot could be found in the spider plot. The presentation of the parallel coordinate plot to someone with limited to no experience with these kinds of plots could read, at first sight, the plot as a line plot. Therefore, the reader could interpret the deviation of the lines as an increase of decrease of the value of the parameter. An alternative could be the spider plot. In this plot, the different parameters are situated around a centre as can be seen in Figure 0.5. Because everything is centred the most influential parameter would be identified by the peak value to the outside of the spider plot. A drawback, however, the number of parameters is limited because too many parameters could lead to too many axis what eventually influences the readability of the plot itself.

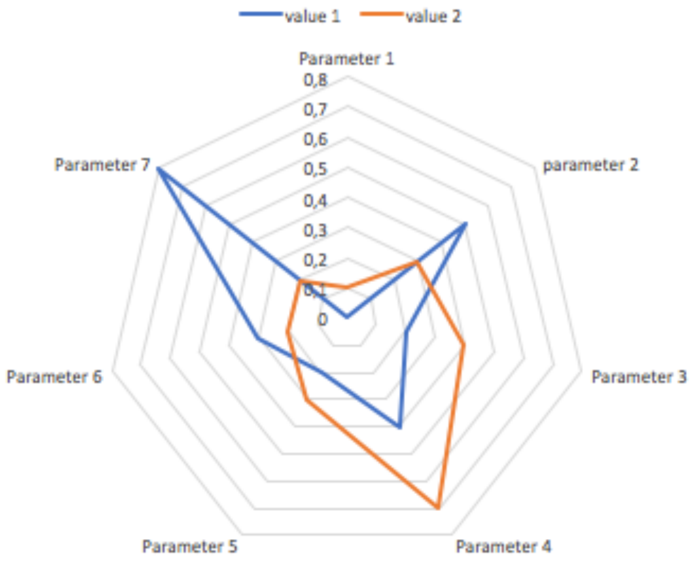

Figure 0.5 Spider plot or radar plot as alternative for the parallel coordinate plot

For the identification of the interaction between different parameters, the bar plot is used. The interaction between two parameters, based on the percentage of one parameter and all other parameters, could give different outcome when determining the percentage when comparing with another parameter. Plotting all possible interactions in one bar plot would give an unlikely long bar plot, what would eventually be not readable anymore. An alternative could be a variance of the hyperbolic tree [Figure 0.6]. In this case, all possible connections will be made, the thickness of the line indicates how strong the interaction between the parameter is. A drawback of this visualisation tool is, is that the line thickness is hard to quantify for the user as well that to many possible interactions can lead to unreadability of the graph because of the many lines.

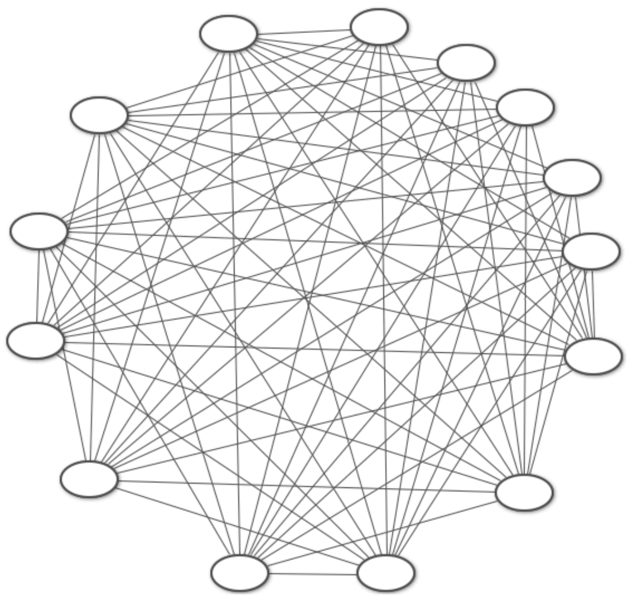

Figure 0.6 Example of the hyperbolic tree in combination with figure 2.2

The most influential combination between two parameters is situated in the current situation in bar plots. The bar plot is split into sections for parameter one, and colours for parameter two. With the bar plot, it is easy to see which combination has the most influence on the performance indicator. A drawback of this plot is that the user must know which parameter indicates the section, and which parameter is situated in colours. A quick scan over the graph will possibly be not enough. An alternative of this plot could be a surface plot. This plot is a 3D-plot which situates the two parameters on the x-axis, and y-axis and the influence rate [%] on the z-axis. In this case, it is possible to see quickly which combination is the most influential combination between two parameters on the performance indicator.

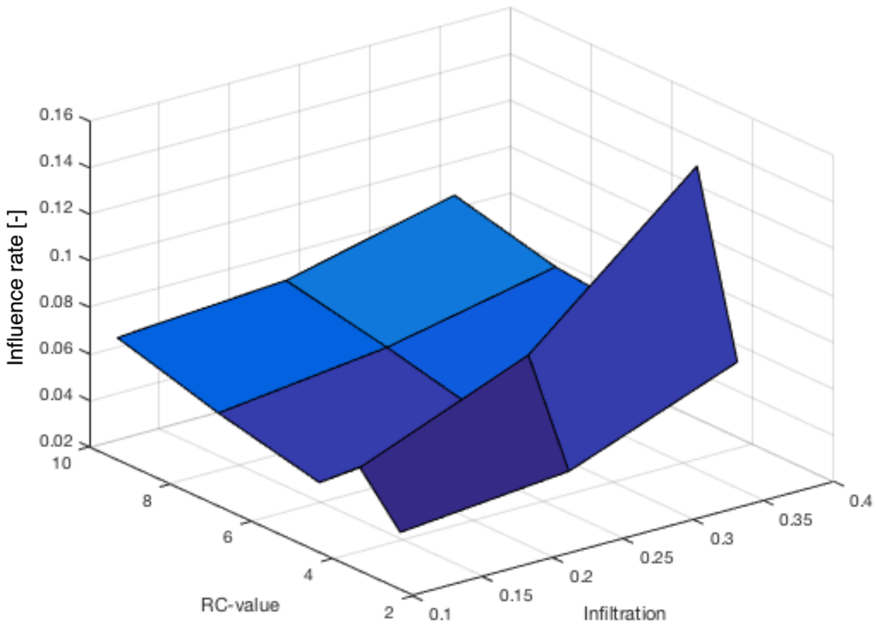

Figure 0.7 Surface plot of two parameters and the influence rate on a performance indicator as replacement of the bar plot

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