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Sensitivity analysis for investigating the energy performance of a retrofitted kindergarten under different weather scenarios

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Extract:

Sensitivity analysis is a technique that aims at estimating how the uncertainty in the independent variables of a mathematical model effects a particular dependent variable given a predefined set of assumptions. This method can be used in building performance analysis for effectively assisting the model development useful to support the design and assessment of high-performance buildings.

This project aims to use sensitivity analysis in combination with building performance simulation to investigate the impacts of different building parameters on the energy use of a high-performance building model compliant with the new Norwegian guidelines for calculation of energy performance of buildings named NS3031 (TEK-10). The first challenge of this project is to efficiently combine the tools for building performance simulation and sensitivity analysis. The second task will be to perform the sensitivity analysis on a calibrated building model. Finally, the performance of the building model will be analyzed under future weather projections, and statistical methods will be used to study to what extent the building performance is affected by climate change.

Keywords:

1. Sensitivity analysis
2. Building performance simulation
3. High-performance buildings

Håkon Eggebø

PREFACE

This master thesis is written as the final semester project of the five-year Master of Science program of Civil and Environmental Engineering (Bygg– og Miljøteknikk) at the Norwegian University of Science and Technology (NTNU) during the spring term of 2017.

The development of this thesis has been an incremental process, starting all the way back in the spring semester of 2016, with the introduction to building performance simulation in a course held by my supervisor, prof. Salvatore Carlucci. After this course, I was privileged to be invited to join a summer school in Shanghai, focusing on sustainable energy in cities, further increasing my interest for building performance simulation. Following the summer school, a project assignment was initiated, running a literature study on Sensitivity analysis used to support building performance analysis, eventually leading up to this master's thesis.

The purpose of this project was to investigate the use of sensitivity analysis used to support building performance analysis by coupling it with building performance simulation tools, and to develop a generic platform to run it with the dynamic simulation engine IDA-ICE. However, the final goal of the project was to run the sensitivity analysis on a case study suitable for investigation. Even though the project started out with a tool, and developed the application for it as a secondary objective, the case study has been a success. It has highlighted interesting aspects about the investigation of energy use in buildings under future weather projections, and proven that the generic platform for sensitivity analysis is working.

I would like to thank my supervisor Professor Salvatore Carlucci for guidance, advice and feedback on everything from sensitivity analysis, building simulations, scientific writing and the road from being a student to a professional. It has been inspirational working together on this project. I would also like to thank Associate Professor Mohamed Hamdy, my co-supervisor, for his invaluable input on the technical aspects of the project. This project could not have been done without your insight in both building physics and computer science combined. You have taught me the value of a multi-disciplinary expertise. A big thanks to Amin Moazami for helpful discussions on the topics of climate morphing, and so many other aspects of this project. I Would like to thank Multiconsult, and especially Ann-Helen Johannessen, for investing their time and effort in my project. Having an office environment to work on the thesis in has been a huge help.

A big thanks to my supportive family, I am lucky to be surrounded by your encouragement and contribution both in writing and reviewing this thesis, and moral support through my years as a student. I would like to thank all my friends here in Trondheim making my time here memorable, it has been a true delight spending the last five years together.

Finally, I would like to thank my wonderful supportive girlfriend Gunhild Fjeld, and our dog Loke for moral support, technical insight and motivation. Especially when I have been living in Trondheim, and Stavanger seemed far away, your voice made it all work.

Trondheim, June 2017

Håkon Eggebø

ABSTRACT

Sensitivity analysis is a technique that aims at estimating how the uncertainty in the independent variables of a mathematical model effects a particular dependent variable given a predefined set of assumptions. This method can be used in building performance analysis for effectively assisting the model, useful to support the design and assessment of high-performance buildings.

This thesis is and investigation on the use of sensitivity analysis to support building performance analysis, with regards to a high-performance building model. The project is divided in two parts. The first part aims to develop the necessary programming infrastructure for running a global sensitivity analysis, and buildings a general platform to automatically perform it. This part investigates the computational efficiency of the simulation approach, the numerical instabilities and technical issues concerning the global sensitivity analysis.

The second part pivots around a case study that is used to test and fine-tune the platform on a high-performance building model compliant with the new Norwegian guidelines for calculation of energy performance of buildings named NS3031 (TEK-10). A key aspect of the investigation is to run the simulation for a series of different weather files to investigate the implications of local climate variations and of future weather projections on the energy performance of the case study through the sensitivity analysis.

The outcome of the analysis is presented using sensitivity indices that quantify the individual impact of the input variables on the energy performance of the building model, for each of the climate scenarios. The outcome of the development phase is a general platform for running a complete sensitivity analysis through the whole-building and dynamic energy simulation software IDA-ICE.

The main findings of this project are an over-all importance of the energy system side of a building on energy performance of the building, while the building envelope showed a lesser impact than expected that is explicable due to the high requirements foreseen by the new Norwegian TEK-10. Regarding the different weather scenarios, the sensitivity analysis shows that the same set of variables are the most sensitive for the building’s energy use in present, future and local climates, even though the magnitude of the effect is different in all the tested scenarios. According to the finding of this project, the new Norwegian standard TEK-10 offers a robust set of design requirements against specification uncertainty under future weather projections and in two different Norwegian climate zones. Furthermore, such TEK-10 requirements appear to have already optimized with respect to robustness the main design variables related to the building envelope and, hence, the design variables that affect the most the energy performance of TEK-10 compliant buildings are those related to the energy systems.

SAMMENDRAG

Sensitivitetsanalyse er en teknikk som estimerer hvordan usikkerhet i en uavhengig variabel påvirker en avhengig variabel, gitt et sett med antakelser. Denne metoden kan bli brukt innen bygningsanalyse for å effektivt vurdere en bygningsmodell i forhold til termiske egenskaper og energi ytelse. Sensitivitets analyse kan da fungere som et verktøy for å bedre planlegge og forbedre høy-ytelses bygg.

Denne oppgaven er et forsøk på å utforske hvordan sensitivitetsanalyse kan bli brukt innen bygningsanalyse, med fokus på høy-ytelses bygg. Prosjektet er delt opp i to hoveddeler; Først å utvikle de nødvendige verktøyene for å kjøre en global sensitivitetsanalyse og utvikle en plattform for å gjennomføre den automatisk. Denne delen vil i hovedsak fokuserer på beregningshastighet, numerisk ustabilitet og tekniske problemer knyttet til sensitivitets analyse.

Del to vil omhandle en case studie, der plattformen som ble utviklet i del en vil bli testet. Case-studiet er en gjort på et bygg designet i henhold til energikrav i de norske byggetekniske forskrifter (TEK10) i henhold til standarden NS3031, oppdatert januar 2016. Et viktig fokus området for denne undersøkelsen er å gjennomføre sensitivitetsanalysen ved flere forskjellige vær scenarioer, for å vurdere hvor robust designet er i forhold til klimaendring, både lokalt og globalt.

Resultatet av denne analyses vil komme i form av en serie med sensitivitets indiser, som forklarer den individuelle betydningen av input variabler på energi ytelsen til ett bygg for hver av de utvalgte klima senarioene. Resultatet fra første fase vil være en plattform for å kjøre sensitivitets analyse gjennom programvaren IDA-ICE.

Hovedfunnet i dette prosjektet er hvordan systemsiden av et bygg dominerer sensitivitetsanalysen, mens bygningskroppens betydning har mindre utslag. I forhold til ulike vær scenarioer viser prosjektet at de samme variablene skiller seg ut som viktige for både nåværende, fremtidige og lokale klima.

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LIST OF ACRONYMS

ACOSSO	Adaptive Component Selection and Smoothing
ANOVA	Analysis of Variance
BPA	Building Performance Analysis
BPS	Building Performance Simulation
DSA	Differential Sensitivity Analysis
FAST	Fourier Amplitude Sensitivity Test
GP	Gaussian Process
IC	Influence Coefficient
LHS	Latin Hypercube Sampling
MARS	Multivariate Adaptive Regression Splines
MCA	Monte Carlo Analysis
MSI	Main Sensitivity Index
NSC	Normalized sensitivity coefficient
nZEB	nearly Zero Energy Building
OAT	One-Parameter-at-a-Time
PCC	Partial Correlation Coefficient
SA	Sensitivity analysis
GSA	Global Sensitivity Analysis
SRC	Standardized Regression Coefficient
SRRC	Standardized Rank Regression Coefficient
SSA	Stochastic Sensitivity Analysis
GUI	Graphical user interface
ZEB	Zero Emission Building

INTRODUCTION

Sensitivity analysis is a technique that aims at estimating how the uncertainty in independent variables of a mathematical model affects a particular dependent variable given a predefined set of assumptions. This method can be used in building performance analysis for effectively assisting the model development useful to support the design and assessment of high-performance buildings.

This project aims to use sensitivity analysis in combination with building performance simulation (BPS) to investigate the impacts of different building parameters on the energy performance for space heating and cooling of a retrofitted kindergarten. The retrofit is compliant with the Norwegian standard for calculation of energy performance of buildings, NS3031 [1] that is the standard for the technical building requirements in Norway, herby referred to as TEK-10. The sensitivity analysis will be performed under several different weather scenarios to investigate both regional differences and the impact of projected future weather scenarios due to the climate change.

The importance of investigating future weather scenarios becomes clear in light of the ever-growing evidence of human-induced climate change. According to analysis performed by NASA, the year of 2014 was the warmest on record since the beginning of measured data (1880) [2]. The following two years, 2015 and 2016, were both warmer than 2014, and, so far, 2017 stands out as exceptionally warm [3]. Based on the measurements and climatic models, the working groups of the Intergovernmental Panel on Climate Change (IPCC) have developed scenarios for contaminant emissions and global warming [4, 5]. Adaptation of a morphing methodology presented by Belcher et al. [6] allows for imposing the global warming scenarios on a local weather file to evaluate the impact of future climate on a building model.

The model in question is based on an Italian kindergarten located in Milan and build in the 1980s with a precast concrete system. The building is a good representation of low performance buildings, typically built in this period and earlier. This building has been analyzed in several other publications [7-9] using other approaches and tools. This stands as one of the advantages of using this building, as the amount of field data available can help validating the new building model built in IDA-ICE. For this project, we plan to use IDA-ICE as the designated building performance simulation (BPS) tool. This software is currently not inherently coupled with statistical software to run sensitivity analysis. Implementing this is a major part of the effort in this project. Establishing a workflow to run sensitivity analysis could pave the way for further research using this method and is considered one of the main outcomes of the project itself.

Considering the discussion above, the research questions are:

- *What are the most important input variables in a building model compliant with TEK-10, in terms of impact on delivered energy under different future weather projections and regional climatic scenarios?*
- *How can one perform a global sensitivity analysis on a building model using IDA-ICE as a simulation engine?*

This work is divided into 6 parts, not including this introduction. The first part is a theoretical chapter, where parts of a literature review on sensitivity analysis from a previous unpublished project is summarized. Also, included in the theoretical chapter is relevant background information on concepts utilized in the project. Chapter 2 describes the building model, its calibration process and the retrofit of the original building model. Chapter 3 is a thorough description of the process developed for performing the SA using IDA-ICE as the simulation engine. This technical chapter includes a discussion and evaluation of different methods for speeding up the simulation time, mainly revolved around the concept of parallel processing. In chapter 4, we present the actual experiment and its setup, with emphasis on the selected variables and the chosen distributions.

Chapter 5 is a presentation of the main results of the GSA in forms of tornado. Moreover, starting from the TEK-10 requirements, the possibility to achieve a net zero energy balance is investigated by adding a PV field to the building energy concept. In this case, the load factor related to the PV system is investigated for one of the climatic scenarios. The final chapter is a discussion on the implications of the results, both in terms of the research results and the method developed.

1 BPS-BASED GLOBAL SENSITIVITY ANALYSIS

This project requires extensive understanding of sensitivity analysis as a tool in BPA. In a previous project a literature study on the subject was performed to identify the established methods of GSA, and sensitivity indices. Theory and key findings from this literature study will be included in this section.

As this project uses a calibrated model as baseline for investigation, a short introduction to calibration will also be included. Theory concerning the technical approach to GSA will be presented in chapter 4, along with the description of the method.

Also included is an introduction to the concepts concerning the weather files, both local and future, theory concerning the output variable Load-matching and a short segment on different concepts of zero emission buildings.

1.1 SENSITIVITY ANALYSIS AND AVAILABLE ANALYTICAL TOOLS

According to interview of professional and academics [10], one of the current main drawbacks in BPS tools is the lack of integration of sensitivity analysis packages and optimization engines. With exception of Autodesk's relatively new Green Building Studio[11], no BPS tool offers the integration of SA. This has led to develop several different environment designs that implement a combination of different software packages. What they all have in common is a workflow design and the fact that, at least, two software tools have been coupled to carry out GSA; typically, a BPS tool and a statistical package. These work environments have been, for the most part, developed by researchers and primarily used for research purposes. The fact that a high skill in programming, in BPS modeling, and statistical insight are required for running SA as a part of a building performance analysis has, so far, prevented its widespread use for commercial purposes among building designers and consultants.

1.1.1 Workflow of a typical global sensitivity analysis

The process of SA within building performance analysis can broadly be described in three steps: pre-processing, simulation and post-processing [10]. For the evaluated literature, all sensitivity analyses were performed according to this pattern that is represented graphically in Figure *1*.

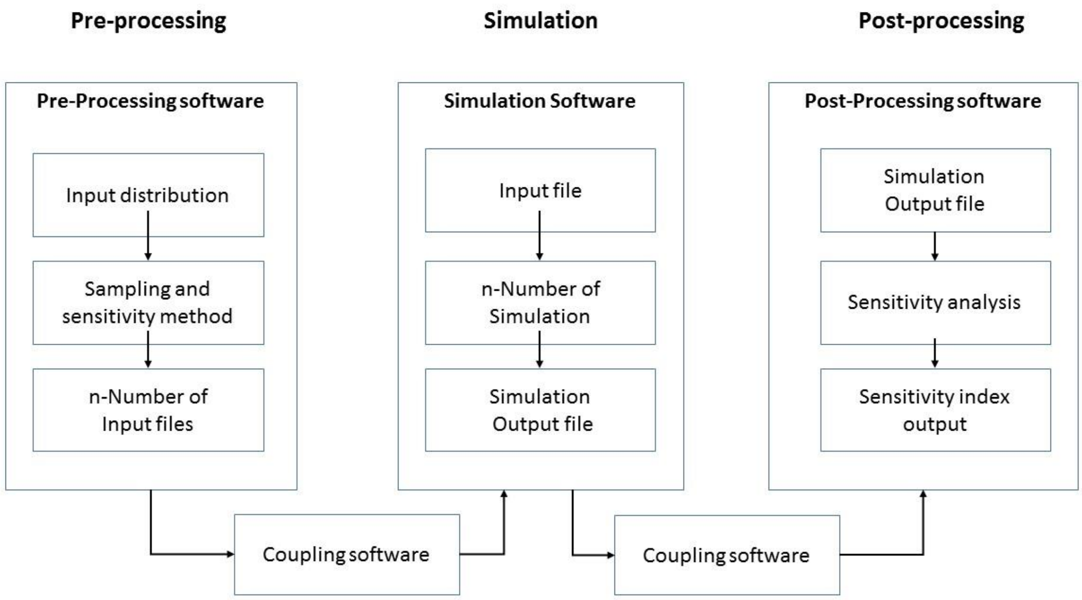

Figure 1: A suggested workflow for Global sensitivity analysis

Depending on the procedure set by individual researchers, several of the boxes in Figure *1* may collapse into one.

1.1.2 An overview of sensitivity analysis methods

A range of different SA methods has been developed in the last decades for a set of different purposes and scenarios. What they all have in common is that they illustrate the impact of change in an independent variable on the dependent variable. Different methods of sensitivity analysis account for different challenges in models, like non-linearity and correlations between variables. BPS-based sensitivity analysis has previously been described, and classification attempts have been proposed in the literature [12-15]. Unfortunately, the proposed classification schemes are non-coordinated and one unique overarching framework cannot correctly respect the grouping rules of all the classifications. Indeed, several overlapping issues rise when trying to sort out the several classification attempts, and numerous SA methods fit in more than one class of classification scheme. Therefore, a presentation of the different SA methods is shown in Figure *1*. It gathers together the several different classification schemes collected from the literature. According to our analysis, the existing classification schemes can be differentiated according to their main purpose: (i) investigation of the propagation effect of the input variable, (ii) problem definition, (iii) type of the analysis carried out, (iv) statistical technique implemented, and (v) sensitivity index used for the assessment.

1.1.2.1 Classification according to the propagation effect of the input variables

Heiselberg, Brohus [16] classify SA methods considering the propagation effect of an input variable and grouped them in three classes: *local sensitivity* (LS) *methods*, *global sensitivity* (GS) *methods* and *screening methods*.

The *LS methods* focus on the estimation of the impacts of given variables affecting a base case [12], iterating one variable at the time. Therefore, LS methods assume the linear dependency between the dependent variable (also called here *output*) and the independent variables (also called here *input*) of a mathematical model. Models fitting in this class are *Adjoint modeling* [17, 18] and *Automated differentiation* [19]. LS methods are computationally inexpensive [10], but they examine only small perturbation in the input and explore only a limited part of the problem space. LS methods typically measure the sensitivity of a model by contrasting the change in the output with the change in the input. Based on this approach, two sensitivity indices are typically used to measure model sensitivity: the *Influence coefficient* (IC) - described later in Section XXX - and the *Normalized sensitivity coefficient* (NSC). The difference between the two indices is that NSC allows for comparison of effect between variables.

LS methods often implement the one-factor-at-a-time (OAT) approach [20] that consists in changing the value of only one independent variable (input) at the time, keeping the others independent variables at their nominal values, and evaluate which is the variation that this produces on the dependent variable (output). The OAT method is mainly found in early SA works on building performance analysis due to its simplicity; indeed, it avoids using any statistical distributions and results to be less computationally heavy than other methods. However, this method is not robust, because results are strongly dependent on the values chosen for the analysis, and not general, because the outcome cannot represent the general behavior of the model, but it only provides a local pattern relating to the investigated area of the problem space.

The *GSA methods* assess the impact of an input variable by changing all the other input variables as well. This makes them partly more robust than LS methods and often a preferred choice for SA. However, GSA methods usually require to generate and run a large number of model simulations resulting a lot more computational expensive than LS methods, and their efficiency is one of the major barriers for the application of Global SA in simulation-based design [21]. Detailed information on Global SA methods can be found in [22, 23].

The *screening methods* use to fix some input factors from a large number of factors without reducing the output variance [24]. The most relevant screening method for BPA is the Morris method that was first described in [25]. The Morris method uses a smaller number of iterations than other global methods and is computational inexpensive. The drawback with the Morris method is that it cannot quantify the combined effects of different factors on the outputs [12]. The Morris method presents its outcome using the mean of the absolute value of the elementary effects (μ_j) and the standard deviation of the elementary effects (σ_j), as sensitivity indices. μ_j measures the influence of the j^{th} independent variable on the dependent variable, and σ_j measures the interaction or non-linearity of the j^{th} independent variable with respect to the dependent variable [13].

1.1.2.2 Classification according to the type of analysis

Lomas and Eppel [15] develop their classification scheme on the typology of the analysis carried out. They categorize SA methods in three classes: differential sensitivity analysis (DSA) methods, Monte Carlo analysis (MCA) methods and stochastic sensitivity analysis (SSA) methods.

The *DSA methods* are widely used because it enables the sensitivity of the model outputs subject to the changes of the input variable to be explored directly [15]. DSA keeps a base case of input variables constant and changes one variable at the time, to analyze the individual impact of that parameter. This method does not account for co-dependencies. However, it is computationally less costly than global analyses, and it was proved to be reliable in several publications [15, 26, 27]. DSA can be easy to implement and understand, but it is not suited for complex analyses that include interdependencies.

MCA is a broad class of computational algorithms. Their key aspect is using randomly sampled input variables from a given distribution to perform numerical calculation. The distribution can be any statistical distribution or a simple uniform distribution, depending on the purpose of the sensitivity analysis [12]. For usage in thermal simulations, MCA demands a more complex implementation, but it does not demand that the system is linear [15].

The *SSA methods*, like DSA, seek to generate sensitivity of predictions as the response to an individual uncertain parameter [15]. What differs from DSA is that SSA changes randomly the input variables for each time step in a way more related to MCA. This results in a complex mathematical model that accounts for co-dependencies. The downside of SSA is that it is both mathematically complex and hard to implement. The SSA *methods* are not widely present in the literature that addresses building performance assessment because of the challenge in implementing it with BPS.

1.1.2.3 Classification according to the problem definition

Closely related to classification by type of analysis, is the classification scheme proposed by Nguyen and Reiter [20] and Saltelli, Tarantola [24]. It addresses the SA problem definition introducing two classes: *mathematical methods* and *probabilistic methods*.

The *mathematical methods* are closely related to LS methods and include the Morris method, differential sensitivity analysis (DSA), and Nominal range sensitivity analysis. Most of the mathematical methods use the OAT approach [20].

The *probabilistic methods* include the Monte Carlo analysis (MCA) methods and the stochastic sensitivity analysis (SSA) methods. The key aspect of the probabilistic approach is using a statistical sample rather than OAT.

1.1.2.4 Classification according to the implemented statistical technique

SA methods can be classified according to statistical techniques used to develop the interaction model. The most common classes are regression-based methods, variance-based methods, meta-model-based methods, screening methods, and graphical methods.

Graphical methods are the most familiar methods of SA. This includes using charts and graphs to visualize the sensitivity of a model. The most common way is to graph data on a scatterplot. A scatterplot is simply plotting the values of independent and dependent variables for a number of simulated cases. Using quantitative measures from the scatterplot, like least square method, or correlation metrics, is a move towards the domain of regression-based methods. Within BPA, the graphical methods are commonly used to support other methods [20].

Regression-based methods involve linear regression applied after that a MCA is performed and are the most common sensitivity analysis in building energy analysis [12]. It is generally fast to compute and easy to understand. Some of the most relevant regression indicators are the Standardized Regression Coefficient (SRC), the Partial Correlation Coefficients (PCC), the Standardized rank regression coefficients (SRRC) and the Partial Rank Correlation Coefficients (PRCCC). Of the four SRRC is the most commonly used, because it can be used for non-linear relationships between input and output of the model. However, both SRC and PCC have been used together with several building performance simulation tools [12].

Variance-based methods aim at decomposing the impact on the output and attributing it to a set of inputs. The two main sensitivity indices used in this approaches are the first-order (*FO*) and the total effects (*TE*) [12] although several different names are used in literature for referring to these two metrics. The difference between the two is that total effects account for interactions amongst inputs. Variance-based methods usually require a high computational cost, but can account for non-linear effects. The two main methods within variance-based SA are the Fourier Amplitude Sensitivity Test (FAST) and Sobol method. FAST does only account for the first order effects, but is hence not excessively computationally heavy. An extended version of FAST, called eFAST, was introduced by Saltelli, Tarantola [28] and was used by Pianosi, Beven [29] in junction with BPS to account for the total effects. Another approach to including total order sensitivity in the variance-based SA is by combining FAST with the analysis of variance (ANOVA) technique [30]. It is called Sobol method and was introduced by Sobol [31] and extended by Saltelli [32]. It accounts for the total order sensitivity assessment, but, in general, results computationally heavier than other global sensitivity analysis methods [33]. However, all these methods require large samples or lengthy numerical simulations to compute model sensitivity because are not analytical techniques and were developed to tackle general functional relationships without considering sample size needed to get a suitable accuracy [23].

Meta-model-based methods are relatively new in the field of building performance analysis [33], but have already been successfully implemented [34, 35]. A meta-model, or *emulator*, is a simpler statistically fit function of a complex model that predicts the simulation output based on the input variables values [36]. A meta-model-based method is a two-stage process. First, a meta-model is created. Next, when a working meta-model is in place, a variance-based SA can be used for completing the sensitivity analysis. The advantage of meta-modeling is the simplification of the simulation part that is replaced with a black-box function describing the model behavior in a computationally efficient way. Typically this methods are analytical techniques that eliminate the need of sampling and, hence, the random errors due to it [21]. However, they assume that the accuracy of the meta-model is satisfactory and may require extra computational cost in building the meta-models. Some available meta-model methods are: the Multivariate Adaptive Regression Splines (MARS), support vector machine, Polynomial Chaos Expansion (PCE), Gaussian Process (GP), Treed Gaussian Process (TGP) [12] and Chen et al.'s method [21]. In general, meta-model-based methods are providing evidence to be suitable for computationally heavy analyses, as shown in [34], where other methods would have resulted too time consuming.

1.1.3 Sensitivity index

Finally, a finer distinction within the SA methods can be based on the sensitivity indices that are actually used to measure and display the sensitivity of a model to its independent variables. These indices are basically statistical quantities. A general sensitivity index is the *Influence coefficient* (IC), also called *Sensitivity coefficient*, which is defined as the first-order partial derivatives of the model output – that is the dependent variable (V_{out}) – with respect to the model input – that are the independent variables (V_{In}) [37].

$$IC = \frac{\text{Change in output}}{\text{Change in input}} = \frac{\partial V_{out}}{\partial V_{in}} \approx \frac{\Delta V_{out}}{\Delta V_{in}}$$

All other sensitivity indices are variations of this derivative, which are adapted to either the chosen sampling method, the model specificities or the research goal. A distinction between sensitivity indices and method for calculating sensitivity indices could be made. This can be exemplified with how IC is a method for calculating a first-order sensitivity indices or linear sensitivity indices.

Several reviews in statistical studies already focus on these families of statistics [13, 20, 24, 33], but, in this work, we intend to collect information limited to those indices that have already been used and better fit in the needs of BPA.

Table 1: A few classification schemes used to classify sensitivity analysis methods.

Heiselberg and Brohus's classification	*Lomas and Eppe's classification*	*Nguyen and Reiter's and Saltelli and Tarantola's classification*	*Classification based on the statistical method*
Local	DSA	Mathematical methods	Graphical
- OAT	MCA	Probabilistic methods	*- scatterplot*
- Adjoint modeling	SSA		OAT
- Automated differentiation			Regression-based
Global			*- SRS*
Screening			*- SRRC*
			-PEAR
			-SPEA
			-PCC
			-PRCC
- Morris method			*- t-value*
			Variance-based
			- FAST
			- eFAST
			- Sobol
			- Extended Sobol
			Meta-model-based
			- MARS
			- PCE
			- GP / TGP
			- Chen's et al.'s method
			- ACOSSO
			- SVM

Table 1 Summarizes the different classification schemes presented in the previous section and sorts them according to their classification.

1.1.4 Available sensitivity indices for this project

In this research, the statistical software package SimLab 2.2 is established to run the sensitivity analysis. It only integrates a few of the aforementioned methods. Specifically, it offers the calculation of SRRC, SRC, PEAR, SPEA, PCC and PRCC for the regression-based methods, and integrated the FAST, eFAST and SOBOL methods for the variance-based methods. Regression-based methods can use the same sampling method for all indices, while the variance-based methods require specific sampling for each method. This make all regression based indices easily available for evaluation after one simulation run, which can be an advantage.

1.1.5 Sampling methods and distributions used for the input variables

Most of the GSA methods, the MCA methods and the probabilistic methods are sampling-based methods. These are methods in which the model is executed repeatedly for combinations of values sampled from a distribution of input factors [14]. There are a number of different distributions available for expressing an input factor. However, the two main approaches are either using a *discrete distribution* provided by the user or using a *probabilistic distribution* drawn from a given problem space. Discrete distribution can be used for input variable like window constructions, where a limited number of options are available and each one is as likely as the next. Probabilistic distributions are relevant if the input variable is continuous, and there is a higher likelihood of choosing within a certain range of the distribution. Sampling from continues distributions can be done pseudo-randomly or by using a sampling method. The dominant method of non-random sampling is the *Latin Hypercube Sampling* (LHS). This method is meant to ensure higher diversity in lower number of draws from a distribution. For regression-based methods, one must use some sort of pseudo-random sampling, and LHS is often preferred. For variance-based methods, the sampling method is given by the SA method, for instance, Sobol requires Sobol-sequence sampling and FAST requires FAST-sampling and so on.

In the case of either continues or discrete and uniform or probabilistic sampling, choosing the problem space to sample from, highly effects the outcome of the sensitivity analysis. In the literature review two main approaches have been identified for choosing the distributions and sampling space. The first is a systematic approach, where one uses a percent-wise area on each side of the expected value for defining the distribution. This has been done by Hopfe and Tian [10, 38, 39], where Hopfe used 10 % of the expected value as standard deviation to describe a Gaussian distribution to draw a LHS from, and Tian used a semi-systematic percentage slightly depending on input for the same type of distribution.

The other approach to sampling is a less systematic approach based on expectation from the building model. For example, you can expect the insulation thickness of a high performance building to be within a certain range, not varying percent-wise in the same manner as indoor air temperature. This method requires individual evaluation of distributions and interval range for each input variable and is commonly used for design purposes when the variability of the benchmark is estimated as a function of different design options [15, 20, 21, 40, 41].

1.1.6 Sample size and model evaluations

The choice of Sensitivity indices and sampling method depend on both the research question and available computational resources. In general, the computational requirement for sensitivity indices that accounts for non-linearity is higher than those focusing on just linear problems.

The smallest sample for the Sobol test is given by $n\,(2k + 2)$, where n is the minimum model evaluations for testing one individual effect [20] and k is the number of variables. For Fast indices the minimum sample size is set to $65k$, where k is the number of input variables [42]. The Simlab 2.2 reference manual [42], recommends a sample size of 1.5–10 times the number of input variables without stating why. However, Nguyen [20] found that a small sample size worked fine for SRC, PCC and PER with monotonic functions, but not for SRRC and PRCC. For these last two indices, convergence was met at a sample size around 100 times the number of input variables.

1.1.7 Results from literature review

From the unpublished literature review of 32 publications relating to BPS and SA, a few key findings will be presented. The findings serve as a basis for establishing the workflow and focus areas of this project. As this project aims to make a functioning coupling between IDA-ICE and SimLab 2.2, it is of importance to investigate which aspects other publications have included in their analysis.

1.1.8 Input and independent variables

The criterion for choosing the publications covered by this review was that SA should have been used in combination with BPS. This means that most of the publications have some form of input and output data from a building model. An attempt to classify these inputs has been made in this section to give an overview of the priorities of researchers in SA so far.

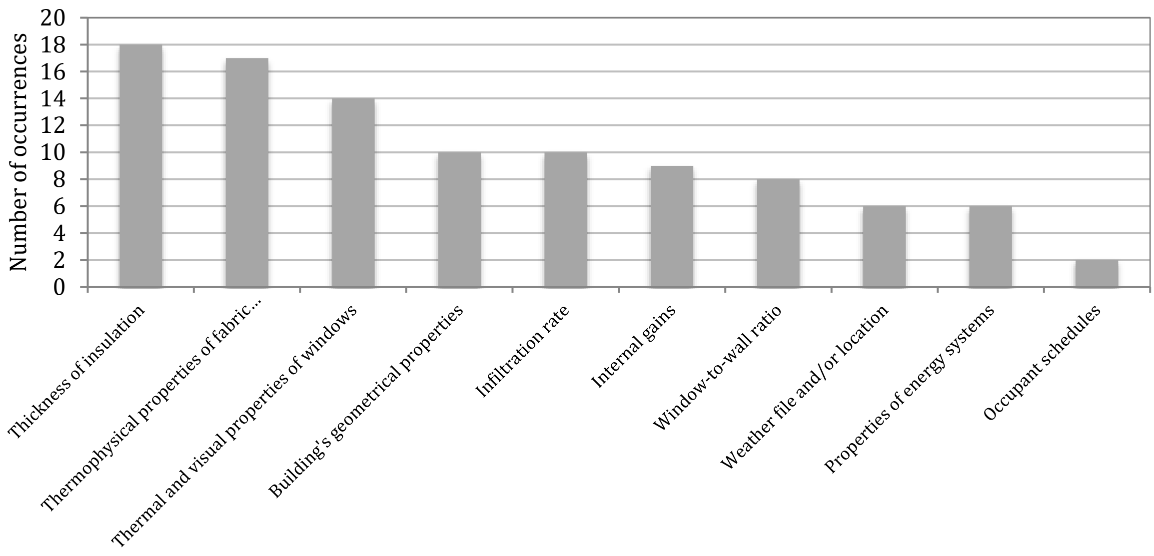

Figure 2: Input variables categorized and counted for the evaluated publications

Thickness of insulation is a category including analysis of U-values for building envelope components. U-value is dependent on physical properties of fabrics; however, U-value varies by just changing the thickness of insulation. The *building geometrical properties* account for room and zone size as well as shape. *Internal gains include* occupant load and schedules, in contrary to *occupant behavior* that examines the impact of occupant usage of and interaction with a building. *Weather file and location* takes into account all the geographical and environmental factors that influence the building performance. The *properties of energy system* is a broad category, accounting research done on efficiency of energy system, choice of energy system, distribution of heating and cooling, operation of energy system and energy gains.

All the analyzed data includes several different input variables, over several of the categories presented in Figure 2. The majority of the publications included thickness of insulation, physical properties of fabrics and components and thermal and visual properties of windows. These feature are not only the most influential properties [43], but are also of the easiest to implement.

1.1.9 Output and dependent variable

Five areas of interest were found in the review on output factor. What is more is that they are usually interrelated. Indoor temperature and energy use for space heating and cooling are two aspects of the same thing, because you either set a constant temperature and measure the supplied energy, or set a restriction on energy and evaluate the evolution of temperature inside the building. The variable least connected to energy use is lighting. However, only one of the publications discussed this without any energy considerations [44].

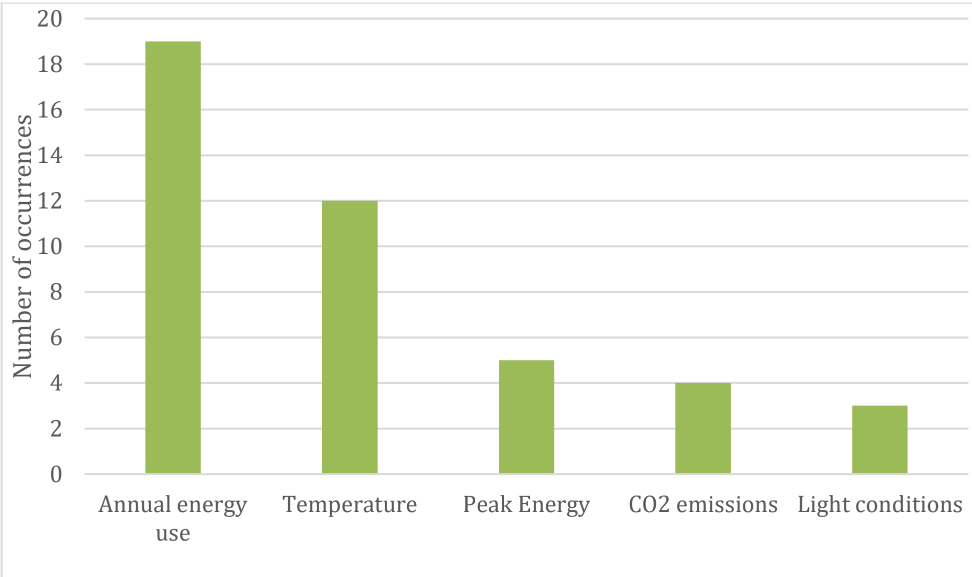

Figure 3: Output variables categorized and counted for the evaluated publications

As somewhat expected, the focus areas for SA in building performance simulation are the energy-related metrics, as shown in Figure 3.

1.2 BUILDING PERFORMANCE SIMULATION

Within BPA, most SAs are carried out running the simulation through a BPS tool. A number of different energy simulation tools are today available on the market. The Building energy software directory [45] lists and rates a total of 147 building energy simulation tools. In addition to the energy tools, several other software tools for analyzing other aspects of building performance are available. In literature, only a few of these simulation tools have been used for carry out sensitivity analysis. The most commonly used are EnergyPlus, Trnsys, DOE, Va114, IES-VE and IDA-ICE. The advantages and disadvantages of each of these tools could be discussed at length, however a general statement could be said: increased level of accuracy demands increased complexity, which in turn increases the need for a skilled user and simulation time.

For this project, IDA-ICE 4.7.1 is the simulation tool used in the analysis described in Section 4. It is a whole-year detailed and dynamic multi-zone simulation application for the study of indoor climate and energy [45]. As this project seeks to develop supplementary functions to IDA-ICE, no other software was considered. However, IDA-ICE is a powerful tool applicable in numerous scenarios. Especially concerning the topics of thermal comfort and energy use estimation. The accuracy of IDA-ICE was assessed through the IEA Solar heating and cooling program task 22; “Building energy analysis tools” [46].

1.2.1 Model calibration

An important part of the building performance simulation in this project is model calibration. The purpose of the calibration is to create a credible building model representing real world building behavior. *Calibration* "is the process of improving the agreement of a code calculation or set of code calculations with respect to a chosen set of benchmarks through the adjustment of parameters implemented in the code" [47]. In this project, the selected benchmarks are measurements from the reference building, further described in section 2. The code calculations would be the building model in this case. The agreement between simulation outcomes and measurements is assessed via statistical metrics. ASHRAE guideline 14 [48] suggests the use of mean bias error MBE, and the coefficient of variation of Root Mean Square Error cvRMSE. Both these metrics have different advantages, so both must be evaluated. If only MBE is used, one could calibrate with high stepwise error if the sum of the error is small. This is not the case for cvRMSE, as it uses squared error.

- Mean Bias Error (MBE)(%): This is a non-dimensional measure of overall bias error between the measured data and simulated data in a known time resolution.

$$MBE = \frac{\sum_i^n (y_i - \hat{y}_i)}{\sum_i^n y_i} [\%]$$

- Coefficient of Variation of Root Mean Square Error cvRMSE(%): This index represents how well the simulation model describes the variability in measured data.

$$cvRMSE = \frac{1}{\bar{y}} \sqrt{\frac{\sum_i^n (y_i - \hat{y}_i)^2}{n}} [\%]$$

y_i= Measured values at instance i

$\hat{y}_i$ =Simulated values at instance i

n = Number of intervals

$\bar{y}$ = Average of the measured data

According to the ASHRAE guideline 14-2002 the simulation model is considered calibrated if it has MBE of 5% and cvRMSE of 15% relative to monthly calibration data. If hourly calibration data are used, these requirements shall be 10% and 30%, respectively. For this project, the calibration will be based on monthly data.

1.2.2 Weather files and future weather scenarios

To run a simulation some boundary conditions must be set. A special set of boundary conditions is the climate data that are imposed to a numerical model of a building via the so-called weather file. One purpose of this project is to estimate the sensitivity of model outputs as a function of varying inputs in different climatic scenarios. In this section, the different relevant weather files will be elaborated.

1.2.2.1 Typical weather files

There are numerous different types of weather files available for as many purposes. Whole-building dynamic energy simulation tools can process weather data on hourly basis (8760 hours in a year of 365 days) to compute building performance throughout the year. In this project the International Weather for Energy Calculation (IWEC) files for the city of Oslo and Bergen is used, based on data collected between 1982-1999 . The data is available in the EnergyPlus Weather format (EPW). The IWEC files are the result of an American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) research project and are available for 227 cities from the US Department of Energy website. The website offers weather files for both Oslo and Bergen in this format.

1.2.2.2 Local weather files

As this project evaluates a standard designed to represent robust building strategies for a country with a divers climate, it is of interest to investigate the difference between local weather files with regards to energy use.

For the research case of southern Norway, we can identify numerous different distinct local weather scenarios. However, only two IWEC weather files for the cities of Oslo and Bergen are available for Norway, Even if the latitude of these two cities is almost the same, the weather is distinctly different. Most of the difference can be explained by two important factors, the proximity to the coast or to the mountains. Bergen and Oslo are separated by a the Scandinavian mountains that force moist air to fall as rain on the west-coast [49]. Moreover, Bergen is a costal-town close to the Atlantic current that stabilizes the temperature fluctuation throughout the year, as seen by the number of degree days at 2850, compared to 3778 for Oslo[50]. The result is a dryer inland climate in Oslo with higher winter and summer extreme temperatures, and a wetter climate in Bergen with smaller seasonal difference [51].

Investigation of meteorological differences and weather patterns are outside the scope of this work, but comparing geographically different weather files can help to evaluate the robustness of the TEK-10 prescriptions with regards to future weather projections affected by the climate change.

1.2.2.3 Climate change scenarios

In this section, we will investigate the future weather files and how they are developed, based on the Intergovernmental Panel on Climate Change (IPCC) projections.

The Intergovernmental Panel on Climate Change has established four socioeconomic possible future scenarios as a baseline for human influence on climate change, which again serves as input in climatic modeling for future weather climate scenarios. These scenarios are further divided into 10 cases each.

- A1: A future with rapid economic growth, global population growth peak mid-century and rapid implementation of new technology. A1 is subdivided based on fossil energy sources intensity.
- A2: A heterogeneous world where self-reliance is the most important factor. A continues increase in population and an economic development regionally oriented.
- B1: Similar population development as A1. Rapid change in economic structure to a more information based economy with decline in material intensity. This case depends on environmental sustainability, without additional climate initiatives.
- B2 emphasizes local solutions to economic, social and environmental sustainability. With less rapid and more divers technological change than B1 and B2. [52]

The climate change projections are different, depending on what scenario is evaluated, so choosing appropriate projections is essential if the goal is to evaluate actual outcome. For this project it is more important to analyze how a changing climate effect the building performance, not how the climate will change, for further discussion on climate change we will refer to IPCC reports [5]

For the third IPCC assessment report published in 2001, the Hadley center developed a climatic model called HadCM3. Based on a model resolution of 3,75 x 2,5 degrees in longitude x latitude, roughly 300 x 300 km. The model offers a series of future weather scenarios based on the different human emission scenarios described above

As the grid generated by the HadCM3 model is much to course for BPS simulations, the morphing technique with local climatic files must be applied. Based on the HadCM3, there are two commercially available software tools that perform this morphing, namely CCworldWeatherGen and WeatherShift. Moazami at al. [53] evaluated the performance of the two in a comparison of three different cities and three parameters. Although some statistical significant difference was found, both tools performed adequately for the purpose of this project. The preferer software will then be the ccworldweatherGen because of previous experience using it.

The CCWorldWeatherGen morhps a local climatic file with the HadCM3 Climate change model for scenario A2 producing weather files for 2020, 2050 and 2080.

One issue identified with this method is the fact that IWEC files and the HadCM3 model are based on weather data collect at different years. This causes a shift in the data. Investigating this shift and its impact is out of the scope of this research, and we will again refer to objective of this project, namely to investigate the impact of different weather scenarios on a building model, not the precision of the climatic data.

1.3 FROM TEK-10 TO THE NEARLY ZERO-ENERGY BUILDING TARGET

The European union have an ambition that all new buildings must near Zero Energy (nZEB) buildings by the end of 2020, and all public buildings must be nZEB by the end of 2018[54]. Since the building investigated in this project is quite advanced in terms of building body and HVAC systems, we wish to investigate if it can achieve requirements for nZEB. To do this, the definition of nZEB must first be investigated

Article 9 of the energy performance of buildings directive [54] requires member states of the European to set national nZEB definitions. In Norway, the research project for Zero Emission buildings have worked on the definition, and delivered their report in February 2016. ZEB [55] is a concept investigating the building Life cycle in regards to emissions. It is based on the notion of producing more energy than the building uses, to compensate for emissions related to materials, construction, use and decommissioning of the building. It requires a more extensive analysis since it investigates emissions, and not energy use. Under the concept of ZEB, several sub groups are defined, depending on the level of detail. The lowest level is ZEB-O, which accounts for the emissions in operation of the building, while ZEB-Complete accounts for all emissions relating to the entire life cycle of the building. ZEB-O is used as the Norwegian definition for near zero energy building

Net Zero Energy Buildings (NZEB) is another strict definition of nZEB that focuses solely on energy, and does not account for construction and decommission. The definition of a NZEB building is an annual energy use of 0 kWh/m^2 primary energy [56]. As this definition uses primary energy the grid loss factor must be accounted for. The annual energy aspect also suggests that the building will have a high degree of grid interaction.

For this project, nZEB will be approach by targeting 0 kWh/m^2 net delivered energy to the building. This is very similar to the NZEB, and the ZEB-O definitions, and is more suitable for this project since it evaluates delivered energy.

1.4 LOAD MATCHING INDEX

To achieve nZEB, a PV system is introduced to balance the energy production with demand on a yearly basis. However, solar radiation is not evenly distributed throughout the year, so it is of interest to investigate the dynamic energy exchange between the building and the electricity grid. Achieving this can be done by using the Load-match index [57].

The load-matching index is calculated as follows:

$$f_{load,i=} \min\left[1, \frac{on\ site\ generation}{Load}\right] * 100\ [\%] \qquad\qquad i = time\ interval(h, d, m)$$

In IDA-Ice the time interval is dynamic, but for simplicity we can choose output time step to one hour. The load and PV-production will then be an average during that hour. For detailed consideration of PV-systems, finer intervals could be preferred, but for this analysis one hour is sufficient.

Since the load-matching index is calculated on an hourly basis, the average load-matching throughout a year is needed. The advantage of using the average is that we can identify the total yearly load-matching index, while still accounting for the hourly data.

2 THE CASE STUDY

This chapter will describe the case study in question, how it has been calibrated, retrofitted, and why it is relevant outside its original intent as a kindergarten in Milan, Italy.

2.1 MODEL DESCRIPTION

The object of analysis is a child care center that host children in the age of 3-36 months. It was built in the 1980's in Milan, Italy. It is a one-story building with a simple rectangular base (44 m long and 24 m wide). The longest sides are facing south-west and north-east (Figure 4) [7-9]. Around 58% of the ground floor is dedicated to children activities, and the rest is used for staff and service areas. The building is characterized by a gross floor area of 944 m^2, a net floor area of 855 m^2; a gross heated volume of 3422 m^2 and a shape factor (S/V) equal to 0.77 m^2/m^3.

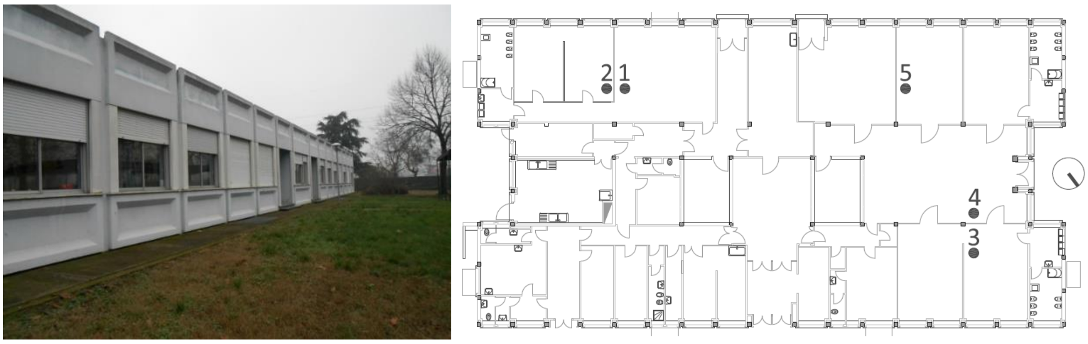

Figure 4. Southwest façade of the kindergarten

The existing building is a typical heavy-prefabricated facility, made of precast concrete panels that include a thin layer of polystyrene foam. The U-value of the wall before retrofit is estimated to be about 1.0 W/(m^2K). The existing roof is a pitched metallic plate with no insulation, placed upon a horizontal concrete slab. The floor is a precast concrete construction slab with a linoleum finishing that divides the heated area from an unheated basement. Both the floor and the roof are estimated to have a U-value of about 1.3 W/(m^2 K). The existing windows are made of an air-filled double-glazing unit, with aluminum frames estimated to have a U-value of 5.8 W/(m^2 K). In addition to the low thermal performance, the windows suffer from a low airtightness, causing high infiltration loss and drafts to occupants. The heating system in place is a natural gas boiler. The overall performance of the heating system is estimated to have a COP around 0.5 from the calibration presented in Section 2.2. This estimation is the result of energy simulations compared to measured delivered energy [7].

2.2 Model calibration

The model in question was thoroughly studied in previous research project [7-9]. These publications were useful to get information for creating the building model in IDA-ICE. This model will be referred to as the calibration baseline model. After the creating of the model, the model outcomes were thoroughly double checked to eliminate errors. Afterwards, it was calibrated with respect to measured energy data. The ASHRAE guideline 14 was used as a reference for the calculation and the cvRMSE and MBE were calculated for the baseline calibration model. For this project lack of scheduling information caused a high degree of uncertainty for the initial calibration, resulting in a time consuming initial calibration. The results of this manual calibration are presented in Figure 5.

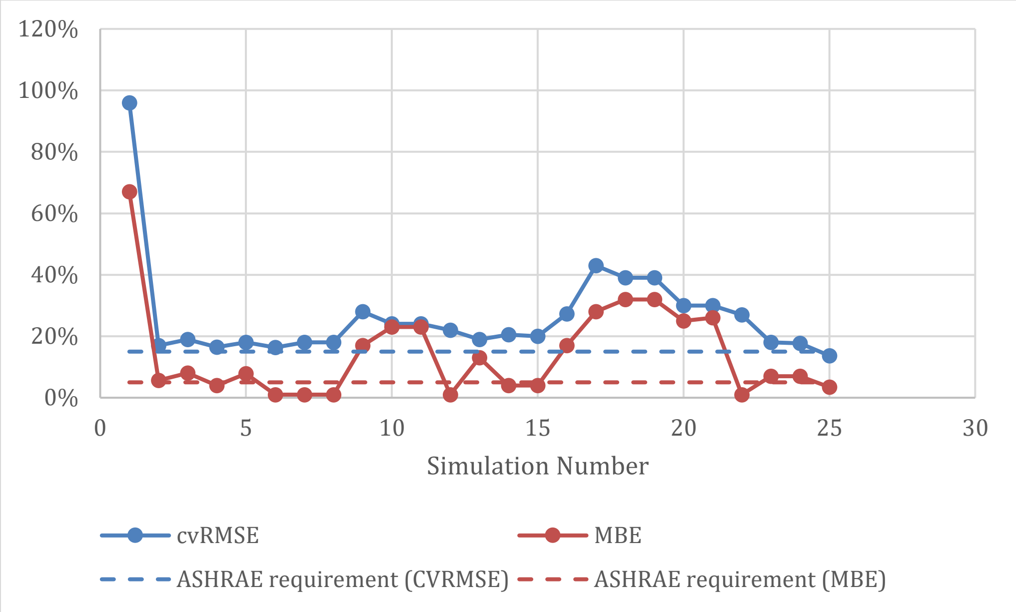

Figure 5: Mean bias error and Coefficient of Variation of Root Mean Square Error values evolvement during calibration process

From Figure 5 we can see that initial simulations offered estimates close to the target values. However, large deviations were found in March and October, and an over estimation of energy use in November and December and an under estimation in January and February prevented further improvements based on building envelope and energy systems. For the next simulations (7-23), several attempts were made to identify possible solutions, leading only to high degree of error. Finally, some scheduling issues were identified which dramatically improved the calibration, providing cvRMSE = 13,7% and MBE = 3,5%, which are sufficient for defining the model as calibrated according to the ASHREA Guideline 14.

2.3 MODEL RETROFIT

As this project aims to analyze a high-performance building in different weather scenarios, a high-performance building model must be obtained. The approach chosen for this work is to suggest an energy retrofit of the calibrated child care building model to achieve the desired performance. The ambition level for the retrofit is compliant with the new energy standards in the Norwegian Building code TEK10 described in NS3031[1].

The retrofit design is made as simplistic as possible, by improving the building envelope, introducing a heat pump with a floor heating distribution system and adding a ventilation system. For reducing the U-value of the opaque components of the building envelope, a glass wool layer with $\lambda = 0{,}034$ W/(mK) is added plus a finishing layer. Heat recovery, SFP, Infiltration and thermal bridge coefficients are set to the selected values in the IDA-ICE GUI, without evaluating actual design solutions.

For windows and doors, the retrofit is less trivial. As glass surfaces are highly important for external energy gains, it is one of the areas for investigation in the sensitivity analysis. Choosing proper glass surfaces for the baseline is therefore of great importance. What we suggest is to choose a commercially available window frame and glazing unit with a U-value of 0,8 W/(m^2 K),

For internal gains the model deviates from the standards to keep in line with the model calibration. This means that internal gains from lights and equipment are slightly lower than the normative values suggested in standards, and the hot water consumption is slightly higher. The internal gains used are collected from the energy bills on which the calibration is based.

Table 2: New TEK 10 energy standards from ns3031 and design values for the building model

Energy metric	Pre-retrofit values	New Tek-10 from NS 3031	Model expected values
U-value of the external **wall**	0.677	≤ 0.18	0.165
U-value of the r**oof**	1.24	≤ 0.13	0.1225
U-value of the **floor**	1.87	≤ 0.10	0.092
U-value windows and doors	5.8	≤ 0.8	0.8
G-value of glazing	0.72	-	0.4
Yearly average heat recovery efficiency	N/A	≥ 80%	70%
Specific Fan Power (SFP)	N/A	≤ 2	2
Infiltration rate **at 50** Pa **[**n_{50}**]**	20	≤ 0.6	0.6
Normalized thermal bridge coefficient	On component level	≤ 0.09	0.09
Air supply rates	Natural ventilation	2-8 $m^3/(m^2 h)$	2-8 $m^3/(m^2 h)$
Solar shading	Manual	•	Automatic solar shading

Table 2 is showing the pre-retrofit design values, minimum design values from the standards and expected values from the model. Keeping in mind that the actual design values will be drawn from Gaussian distributions, only expected values are presented in the table. For the yearly average heat recovery efficiency, a lower value than the standards minimum is used as expected value. This is done because there are very few solutions allowing for above 85% efficiency, and shifting the expected value will allow for a more comprehensive discussion.

2.4 MODEL RELEVANCE FOR EUROPEAN BUILDING STOCK

The kindergarten in question is situated and calibrated for Milan, Italy. It is mainly composed of components called "Predalle" translated to composite floor slabs [58]. The floor slabs are self-supporting, but require additional concrete after mounting on site. The thermal performance of the slabs used in this building is fairly poor $R = 0.28\ m^2K/W$, making them representative for low-insulated concrete loadbearing structures. The walls and internal floors are built on the same principles with low-performance sandwich elements in concrete, and inner walls in brick. In terms of energy and thermal performance this building can be said to represent a number of buildings from the 20th century, as almost 50% of the existing building residential building stock is Europe is built before 1970 [59]. This makes the building ideal for this kind of retrofit analysis.

3 DEVELOPING A GLOBAL SENSITIVITY ANALYSIS PLATFORM FOR IDA-ICE

The use of global sensitivity analysis (GSA) within the field of building performance simulation have been widely used to explore the characteristics of buildings [12]. However, few tools are available for conducting a fully automated simulation-based building performance sensitivity analysis. Tools for running GSA have been developed for popular building simulation software like EnergyPlus [35] and VA114 [14]. In this project, the use of GSA is extended to IDA-ICE –version 4.7.1–, which is a building performance simulation software, commonly used in the Nordic countries. This is made by creating and automated workflow that couples the IDA-ICE's simulation engine with a MATLAB script that is connected to the GSA tool SimLab. While Figure 1 presents a general graphical representation of an automated GSA workflow that is presented in section 1.1.1., Figure 6 shows a more specific workflow for the chosen software environment.

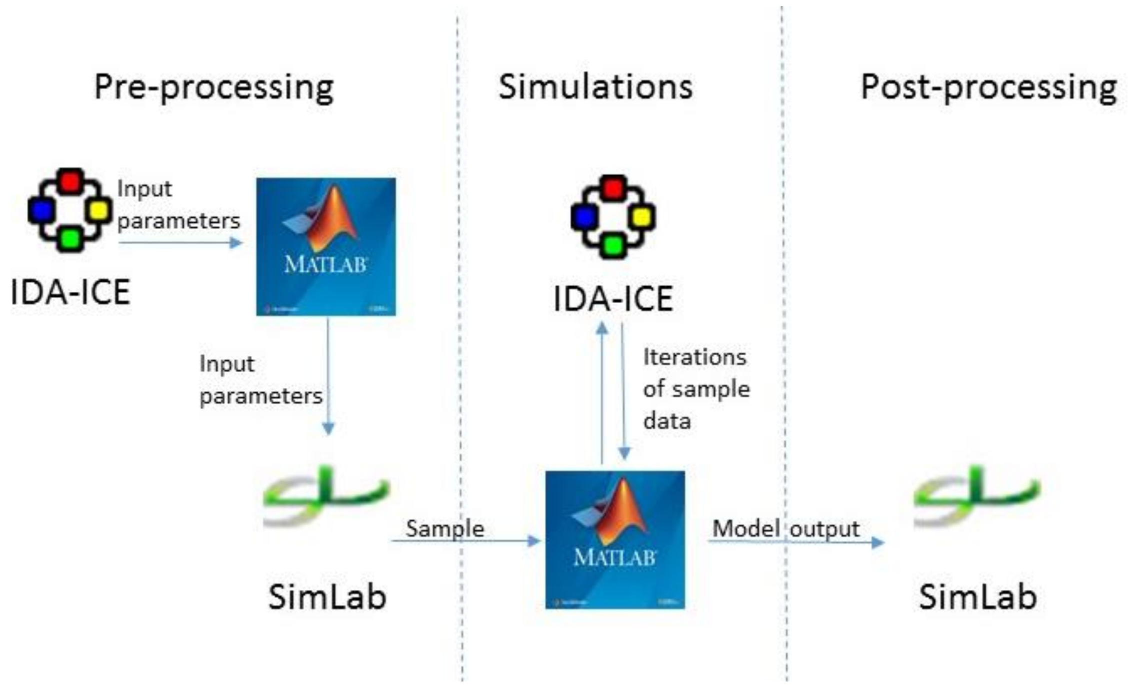

Figure 6 - A suggested workflow for Global sensitivity analysis

The workflow is commonly divided into pre-processing, simulations and post-processing. Within each of these sub categories, actions are performed and information is exchanged between software. The GSA must start with a base case model with all aspects necessary to run established simulations.

For coupling SimLab and IDA-ICE, a method consists in generating txt-files that move data from one application to another and store locally the simulation outcomes. MATLAB scripts typically do this. For this project MATLAB is chosen as a programming environment. Among all the available tools MATLAB had the required flexibility to design a code or set of routines fit-for-purpose. Unfortunately, it is not license free, however it is very commonly used in the research environments. Possibly because of its strength in storing and manipulating data in the form of a matrix

Based on the literature review (section 2.5) SimLab 2.2 is chosen to perform GSA. SimLab 2.2 is a statistical software working in combination with R- another statistical software to perform global sensitivity analysis, developed solely for this purpose [60].

The following subsections describe how the platform has been created and, followed by an investigation of parallel processing, both concerning efficiency and possible propagation of errors. This chapter ends with a short discussion of the optimal setup and use of the platform, for further use in the case study.

3.1 PLATFORM DESCRIPTION

The platform layout is described in Figure 6 through pre-processing, simulations and post-processing. The main challenge in developing the platform is exchanging the correct information between the processes within each of these three steps. A set out automatic functions and scripts in MATLAB make up the foundation of the platform, performing the information exchanges. In this section two concepts of changing and collecting variables in IDA-ICE will be presented, followed by step-by-step guide to running the platform.

3.1.1 Input variables and variable change in IDA-ICE

For IDA-ICE, there are two different methods for automatically changing parameter of the variables of a building model: through diff-scripts or the model solver.

The first is by changing the model input file, and then running a model solver. This runs energy simulation on an existing model, with updated information from an input file. Changes in this input file will result in changes in the model and, hence, in the outcome. This model solver approach is not depended on the Graphical User Interface (GUI) of the software, having the advantage of reduced complexity. The main drawback of the solver-method is a limitation on which parameters can be modified.

The second approach is to use the build-in difference script approach. When a change is made in the GUI, for example insulation thickness, a script is made to forward the changes to the building model, called diff-script short for difference script. Both reading the diff-script and running new ones is available through the GUI of IDA-ICE under tools. By generating diff-scripts in MATLAB the user can implement any desirable model changes through a text based approach, allowing for iterative building modeling. This is the chosen method for this project. The diff-script is generated by changing the desired variable in the IDA-ICE's GUI and running the diff-script tool.

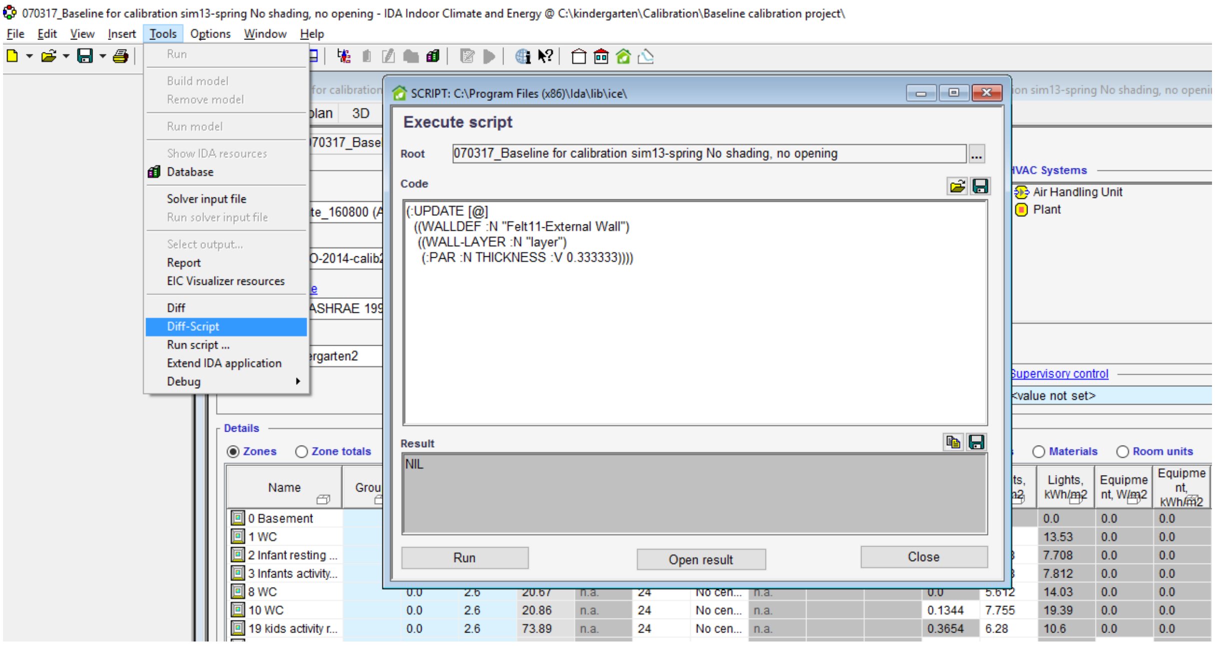

Figure 7 - Accessing the diff-script through IDA-ICE interface

Figure 7 illustrates how to access the diff-script through the IDA-ICE interface, with an example of the script syntax. The syntax is further elaborated in Table 3. The input value of 0.333333 is used as an arbitrary identification value, identified by the MATLAB scripts.

Table 3 - Diff-Script syntax for changing the thickness of a layer in the wall "External wall example"

(:UPDATE [@]	% Update the following
((WALLDEF :N "External wall example")	% Element name
((WALL-LAYER :N "layer")	% Layer name
(:PAR :N THICKNESS :V 0.333333))))	% attribute and value

As the project aims to create a workflow available to users not familiar with the programing language used in IDA-ICE and the diff-scripts it is desirable reduce the recourse of the user to the programing language. Ideally, the user needs only to copy the diff-script to a cms-file in the MATLAB work folder called *diff_script.cms*, with the identification value of 0.333333.

3.1.2 Collecting output variables

When any simulation is complete in IDA-ICE the output, data is stored in a temporary file specified by user in the IDA-ICE's preferences. To run a GSA, specific values from this output data must be collected. The file containing output data is called *ida_lisp.end*. To collect an output value from this file, the variable name must be known. Naming conventions in this file is non-trivial, so the best way to find a certain output variable is to find the output value in IDA-ICE, then search for that specific numerical value in the file, and thereby finding the name of the output variable. For example, if a model has 744 kWh energy used for heating in January, you search the file for 744 and find:

Emeterlochc.Monpospowe(1)   744.0

A few output variable names are already available in the script, but for output variable names not pre-located this would be the method of obtaining them.

The *ida_lisp.end* file contains a summary of data to display in the IDA-ICE interface. If requested the program can output time-step data. These files can be accessed in the post-processing for further evaluation of output data.

3.1.3 Pre-processing

The platform requires some input on file locations and work folders highlighted in the code as well as some pre-defined output variables to collect. The output variables can be any information produced by the simulation software. If the desired output variables are not available in the code, use the method in 3.1.2 to identify them.

If locations of files and output variables of the GSA are set, the script is ready to run. Running the script will start by generating a configuration file for SimLab containing the factors based on the difference script from IDA-ICE, and request the user to open this file in SimLab. It is not required to use the configuration file, the Simlab 2.2 setup can be done manually through the GUI. Follow the SimLab user manual through the necessary steps for generating a sample file, based on the desired distributions for each independent variable and sampling method for all the independent variables.

Sampling generation is the last step of the pre-processing, when the sample is generated MATLAB prompts the user for Y/N to start simulations.

3.1.4 Running the platform and post processing

After pre-processing, MATLAB will now run the full sample simulation and generate the file *output.txt* to be imported to in SimLab. As both the sample and the output is now available, SimLab can generate the desired sensitivity indices depending on the chosen sampling method. Again, for further information for the use of SimLab 2.2, refer to the software manual. The developed MATLAB platform that performs a GSA analysis is reported and made available online together with this publication at the digital archive of the Norwegian University of Science and Technology (NTNU) [61]

3.2 PARALLEL PROCESSING IMPLEMENTATION AND EVALUATION

The original process was very time consuming, therefore the need to reduce the simulation time surfaced. A basic method for reducing computation time is to reduce complexity of the model. One could use a simplified model by introducing a single-zoned model mimicking the thermal and energy performance of the multi-zone building. Another approach to reducing computational time is by increasing the speed of simulation by upgrading the hardware. As the Department of Civil and Environmental engineering at NTNU had a workstation available this method was preferred.

To utilize the full advantage of a workstation, parallel processing had to be considered. Even though this requires more comprehensive programming, it can dramatically reduce computation time. Parallel processing consists basically in running several simulations at once on different cores or CPUs. Depending on the method chosen for parallelization, additional uncertainty can be introduced, so an investigation of the effectiveness of the parallelization method is performed in two parts. First a time consumption test is performed to see what method is faster, then, a test to investigate the propagation of errors for one of the method is performed.

The preliminary work in this research is done on a Samsung 9 series Laptop with Intel i5-3317U 1,7 GHz dual-core and 4 GB RAM. This is sufficient for running single simulations and doing much of the design work. However, for the final simulation runs, with a large sample size, we used a workstation with 2x Intel Xeon E5-2697 V4, with 16 cores and 32GB RAM.

3.2.1 Introduction to parallel processing

As discussed in the previous section, it was desirable to implement parallel computing in the platform. Within computer science there are three methods for running tasks in parallel on a single machine based on its CPU.

The first approach is the *hyper threading*, a method of running parallel processes on a single core on one CPU unit. The CPU pretends it has more cores than it does, and uses its own logic to speed up program execution [62]. This method was developed by Intel in the Pentium 4 series back in 2002.

The second method is using a CPU with multiple cores. This is now considered standard for most CPU's, and is used in combination with the hyper threading technology to maximize the computational potential on most devices today. The laptop utilizes both methods for parallelization with a dual-core CPU and two logical processors from hyper threading for each core, resulting in 4 available logical processors.

The last method for parallel processing is multiple CPU processing. This is available on the workstation. What this means is that the motherboard has two CPU sockets with one CPU in each and the needed software to utilize both. The number of available logical processors for the workstation will then be two logical processors for each core, 16 cores for each CPU and two CPUs, resulting in a total of 64 logical processors.

Lately, the development of running processes in parallel on a Graphical processing unit (GPU) has evolved, but we do not have the necessary hardware to implement this approach as well.

For this project, we have identified two methods of running the sensitivity analysis workflow in parallel. The first method is by using a time-split parallelization method in IDA-ICE. It splits up one simulation into several different time periods, and combining all the results. For a yearly simulation utilizing 32 cores, the simulation could be split up in 32 time periods with its own initial values. A problem with this method is that it requires 32 different initial values, instead of one, propagating the error of initial values in the numerical translations of the original differential equations. The advantage of this method is that it is already available in the IDA-ICE interface and requires little extra work to be implemented.

The second method of parallelization proposed in this research is to run several instances of IDA-ICE at the same time. This will be done through the MATLAB imbedded method of PARFOR loop. It initiates a given number of cores and runs one whole year simulation on each of them, and will be referred to as whole-year parallelization. This method could allow for decrease in computational time proportional to the number of available core, only limited by memory capacity on the computer.

3.2.2 Time saving comparison

The time saving comparison is presented in Table 4. It is divided into two categories, single simulation and sample simulation. The single simulation category is one simulation run with and without time-split parallelization on both the computers. The PARFOR method cannot be tested for single simulations since its advantage is to run several instances at the same time.

The sample simulation test is made of 200 simulations running in series, parallel and in a combined manner, to establish the fastest way to run a large sample. For comparison, an estimation of how long it would take to run the sample on the laptop in series is presented. This is only based on 4 simulation, as it would be too time consuming, and of little interest to run the entire simulation this way.

The bottleneck of parallel processing in IDA-ICE is the available memory for simulation. As IDA-ICE requires a fair amount of RAM, none of the computers can use the maximum of logical processors available. After some trial and error, 20 cores for the super-computer and 2 cores for the laptop was deemed suitable to avoid crashes.

3.2.3 Propagation of error in time-split parallelization

Propagation of errors in time split-parallelization is tested by comparing outputs of simulation without parallelization and outputs of time-split parallelization. The variable tested is the energy used for local heating emitters. Energy use for local heating emitters is depended on the temperature in the previous time step. For each time-period an initial value for temperature is used instead of the value from the previous time-step, resulting in a systematic difference in the data. This is illustrated in Figure 8,

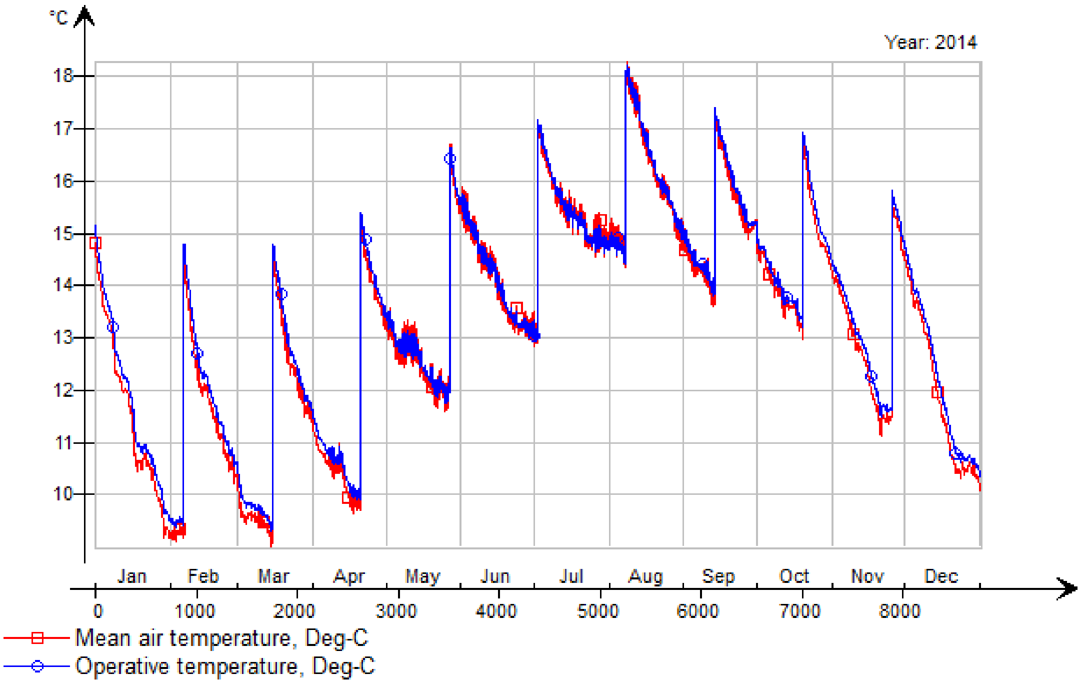

Figure 8 - Temperature in basement over a year visualizing initial values problem of time-split parallelization with 10 CPU cores. The steps in the graph is a result of combining the 10 simulations with initial values causing the step up

Figure 8 shows the time evolutions of the indoor mean radiant and operative temperatures in the basement computed through the time-split parallelization method. The basement is in free-running mode and should be characterized by temperature trends without heavy steps. It is evident the error in the temperature estimation caused by the initialization of each simulation treat. It overestimates both mean radiant and operative temperatures by 3.5–5.5 ˚C. It indicates that without a thorough check of the simulation results, this method demonstrates to be not reliable for investigation of thermal comfort in free-running buildings.

3.2.4 Computational cost

The case of computation time is a big issue in the situation of SA in BPS. This is mainly due to the computational expense of BPS, and the big sample size required by the SA. To find an optimal approach to running the simulations we run a time comparison test based on a sample size of 200, with 23 variables changing.

Table 4: Computational cost of running single and sample simulations a different setup

	Computer	Cores in use	Time (hours)	Time saving (%)
Single simulation	Simulation on laptop	1	0,75	Baseline
	Simulation on server	1	0,71	5.4%
	Time split parallelization on laptop	2	0,45	40%
	Time split parallelization on server	20	0,067	91,1%
200 simulations (i.e., sensitivity analysis sample)	Computing in series on laptop	1	151	Baseline
	Time split parallelization on laptop	2	90,2	40,3%
	Whole year parallelization on supercomputer	20	13,05	91,4%
	Time split parallelization on supercomputer	20	65,5	56,6%
	Simulations in series on supercomputer	1	142	6,6%%
	Combine time split parallelization and parallel in MATLAB on supercomputer	4x5	28,9	80.9%

Table 4 shows the computational time for each tested setup. The different methods vary in time saving because of memory use in initiation of the software, but the main conclusion is that MATLAB-based parallelization is the fastest approach for running a large sample with about 90%-time reduction with respect to the baseline. The setup utilizes only 20 cores of the available 32, to avoid low memory issues.

3.2.5 Propagation of error test

To analyze the quality of the time-split parallelization simulation we can plot the two identical simulation models with different simulation methods, and calculate the mean bias error and the coefficient of variation of the root-mean square error.

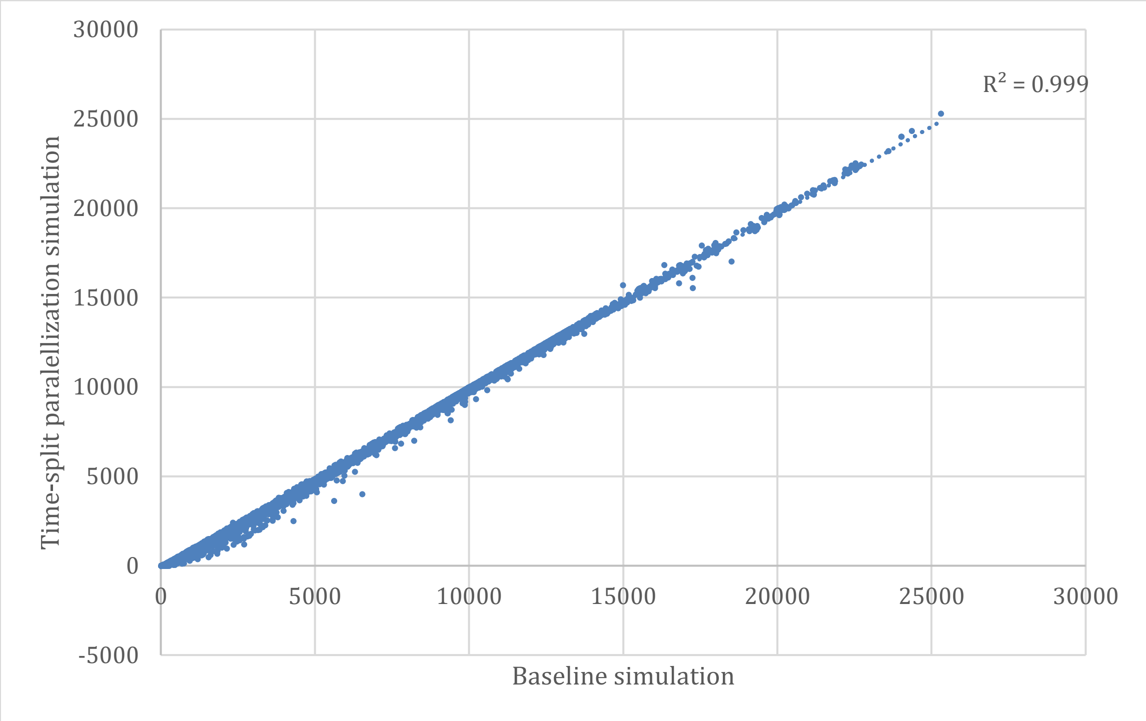

Figure 9: Comparison of the hourly energy need for space heating for time-split parallelization and baseline simulation

Figure 9 shows how the two simulation methods perform compared to each other. If they were equal we would see a straight line x = y in the figure. Looking at the R^2 the linear regression is a good fit to the data points. This indicates that time-split parallelization does not introduce any non-linear issues, and that the data points have a low scattering. However, the mean bias error (MBE = 3,4%) and the coefficient of variation of the root-mean square error (cvRMSE=3.2%), between the two simulations show a noteworthy difference. This indicates a notable difference in outcome for the two methods and can introduce an unnecessary propagation of error.

The MBE also indicates that there is a notable shift in the data. Looking at Figure 9, the time-split parallelization is consequently under-estimating the energy use relative to the baseline simulation explaining the MBE. This under-estimation is not easily explained by the predicted systematic error, and remains a problem for using time-split parallelization.

What is more, the systematic error expected base on the knowledge about the model as shown in Figure 8 is not identified in the data. This indicates that time-split parallelization is not fully understood, and that the behavior of the model introduces some unnecessary uncertainty.

Even though the issues identified can be problematic, especially for simulations regarding overheating hours, the relatively low MBE and cvRMSE makes the method of time-split parallelization suitable for simulations where some degree of error is acceptable. Like comparing different design solutions and early design simulations.

3.2.6 Discussion on parallelization

We can conclude that the parallelization via MATLAB offers the best results both in time reduction, and introduces no additional error compare to running the simulations in series on one core. Time-split parallelization offers results with a marginal additional error, and is a method is preferred in the initial design phase of the model. The propagation of errors can be acceptable for a certain type of simulations; however, when investigating either hourly data or overheating hours it can pose notable issues. Another problem with time-split parallelization is that the model does not behave as predicted, leaving uncertainty about the limitation of the model. In this area, further investigations are recommended before including the method in this type of analysis.

The parallelization is a built-in function in the platform, and no user interaction is needed. MATLAB uses the available processor cores and runs according to the capacity of the computer in question. It is recommended not to use the time-split parallelization in IDA-ICE simultaneously with the whole year parallelization to avoid memory overload problems.

4 GLOBAL SENSITIVITY ANALYSIS SETUP

The global sensitivity analysis in this project is an attempt to investigate what is the most important input variables on energy performance under different climatic scenarios. The global sensitivity analysis will be applied to a numerical model of an kindergarten building, which was first calibrated against monitored energy data, later enhanced according to the requirements of TEK-10, and finally equipped with a PV system to achieve the nearly zero energy target. In this section, the results of the global sensitivity analysis are presented and discussed.

4.1 SCENARIOS FOR INVESTIGATION

The climatic scenarios for investigation are based on the available scenarios from the EnergyPlus database and the application of the morphing tool CCworldWeatherGen. It is of interest to investigate two different local scenarios, governed by the same standards, subjected to different climate conditions. For this purpose, Oslo and Bergen serve as a good comparison, as discussed in section 1.2.2.2. For the future weather scenarios Oslo TMY is used as a baseline and weather projections for 2020, 2050 and 2080 are generated and results of analysis are compared.

4.2 INPUT VARIABLES

Investigating impact factors requires a methodical approach to input variables, distributions and sampling, with realistic values. To obtain these, the distributions have been chosen based on the new Norwegian energy standard for TEK 10 (NS3031), applying a standard deviation of ±10% of the expected values for most cases. The standard deviation is chosen based on the findings in the literature review in section 1.1.5, mostly inspired by Hopfe [38]. Deviating from this approach is the set point temperatures and azimuth of the building. The azimuth had no preferred angle or interval, so it was of interest to cover a wider specter. The setpoint temperatures could not follow a percentwise convention, and suitable ranges were chosen close to the values from NS3031.

Table 5: Initial Input parameters for investigation of TEK-10 model

Metric	Distribution	μ/σ or Range	Unit of measure
1. Wall insulation thickness	Normal	150/15	mm
2.Roof insulation thickness	Normal	250/25	mm
3.Floor insulation thickness	Normal	350/35	mm
4.Air flow rates during operating hours	Normal	8/0,8	$m^3/(m^2\ h)$
5.G-value windows	Normal	0,4/0,04	adimensional
6.U-value windows	Normal	0,6/0,06	$W/(m^2\ K)$
7.Heat recovery efficiency	Normal	75/7.5	%
8.Infiltration rates	Normal	0,6/0,06	ACH
9.Colling set point	Uniform	22±1	°C
10.Heating set point	Uniform	24±1	°C
11.Rotation of building from baseline	Uniform	[98-188]	°
12.SFP	Normal	2/0,2	adimensional
13.Thermal Bridge factor	Normal	0,09/0,009	$W/(K\ m^2)$
14.Solar shading on if irradiance is higher than:	Normal	100/10	W/m^2
15.Thickness inner walls	Normal	150/15	mm
16.System COP	Normal	4/0,4	kW_{heat} / $kW_{electricity}$

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Table 5 contains the different distributions and input values this project implements. Note that the heating and cooling set points vary within a uniform distribution with ±1°C. This is because a percentage change would be problematic in the case of temperature, since we should have used absolute temperatures. The fact that both set point temperatures and building azimuth does not follow the same distribution scheme as the rest of the inputs, must be accounted for in the analysis of the results. Table 7 in the appendix is the actual input values for a selection of cases, based on the distributions in Table 5.

4.3 OUTPUT VARIABLES

From the BPS tool, numerous output variables can be addressed without extra effort after the simulations are done. This allows for future investigations of the dataset with additional research goals.

4.3.1 Delivered Energy for heating, cooling and domestic hot water

For this project the focus area is delivered energy for heating and cooling, drawing the system boundary between the heating and cooling system and the energy grid. The system is a ground to water heat pump with a top up electric heater and floor based water distribution net. Included in the heating system is the domestic hot water requirements. Analyzing the impact of delivered energy to heating and cooling while domestic hot water is part of the output is not problematic, since only one input factors effecting the domestic hot water energy use is the COP, and it can be accounted for during the analysis of the results.

This output will be collected and analyzed in the sensitivity analysis under all the climatic scenarios, for comparison between the different weather scenarios and individual assessment.

4.3.2 PV-Load matching index

For the baseline case of TMY Oslo we wish to investigate the degree of utilization of the PV-system. This is interesting because the PV energy production does not coincide with building energy needs. A consequence of this is onsite PV-system having to sell electricity to the grid at low prices. Maximizing the utilization of produced energy is therefore of interest, and a GSA is suitable to support design in this case. As discussed in section 1.4, there are different approaches to assessing the utilization of PV production. For each of the simulation the hourly energy demand and PV-production will be collected for post processing and sensitivity analysis.

The model PV system is a 400 m^2 solar panel system with an efficiency of 16% producing 66kw at peak performance. The size and efficiency of the PV-system is expected to be the most dominant factor for impacting the load factor, for this reason they are excluded from the analysis, and an arbitrary size suiting the building area is chosen with a common efficiency. The reason for not including size and efficiency in the load factor investigation is that we desire to investigate the building body, and leave energy production systems to experts in that field.

4.4 NUMBER OF ITERATIONS

As discussed in section 1.1.6, the number of input variables must be adapted to the computational power to achieve the results within a reasonable time. Starting with 23 input variables for the model, an estimated calculation time was, for convergent, around 110 hours. Reducing the computational time of the model will allow for investigation of more climatic scenarios. Because of this the variables for investigation was reduced to the 16 most influential factors from a preliminary sensitivity analysis using PEAR indices. The results from this analysis had a different setup in distributions than the final simulations and will not be presented to avoid confusion.

From Nguyen [20] performance review and results from initial models, 600 simulations were selected to obtain convergent results for the various scenarios. The computation time of one full scenario simulation on the supercomputer is around 65hours.

4.5 SENSITIVITY INDICES AND SAMPLING METHOD OF CHOICE

Because of computational complexity this project will aim to use SRC and SRRC as sensitivity indices. From the literature review in chapter 1.1.2 it was found that these were the most commonly used indices. Since the Sensitivity indices quality is dependent on the outcome of the model, a decision on which indices is most suitable will be performed in the results section. In short, if the model is highly linear, SRC will be used. If not, SRRC should be used if the results are convergent. These regression based indices are mainly chosen because they are less computational heavy[20] than methods like Sobol and eFAST, that could be more desirable if computation cost was not an issue.

It was the intention of the author to investigate sensitivity using the regression based sensitivity indices SRC and SRRC. However, after running the complete simulation set it was clear that the SRRC had not reach converges. This was established after comparing the results of SRC and SRRC, and by evaluating each output individually. Nguyen states that: "It is worthy of note that the solutions of the rank transformation SA indices before convergence are completely incorrect, thus the convergence is crucial for their accuracy" [20]. The coefficient of model determination R^2 of the SRC is calculated to 0.951, while the R^2 of SRRC is at 0.087 for the Oslo TMY case. This proves two important aspects. First the SRC has a high degree of linearity, indicating that SRC is a good metric of evaluation. The second point is that SRRC has a very low R^2, supporting the notion that the model has not reach convergence for the SRRC calculation. For the remainder of this project, SRC will be the only indices for investigation, since the model has a proven high linearity, and the results will be reliable.

5 RESULTS AND DISCUSSION

In this section, the findings of the global sensitivity analysis for the reference case are presented. Presentation of the sensitivity index SRC is done through a sorted tornado diagram (butterfly graph) showing individual impacts of each input variable. The tornado diagrams are supported by tables and additional graphs, which will help to further elaborate and discuss a few key aspects.

The section starts by investigating the case of the typical meteorological year (TMY) for Oslo, based on weather data collected from 1982-1999 as described in section 1.2.2.1. For this case, a more in depth investigation will follow to set the sensitivity analysis in a broader perspective. This will include histograms of specific delivered energy and a presentation of several sets of input for a selection of cases.

Following the Oslo TMY case, an analysis of the impact of climate change on building energy use is presented. This section investigates the change in SRC compared to the change in specific energy delivered for space heating and cooling. Investigating the robustness of the TEK-10 standard in relevance to the future climate change is one of the important aspects of this section.

After comparing future weather data with the Oslo TMY, the Bergen TMY is up for investigation. This will be similar to the discussion on climate change, so comparisons to the different future weather files can be made.

The final section in this chapter discusses the concept of nZEB in regards to the TEK-10 requirements. As this project has gathered a large amount of data on building performance, and possible improvements, it is well suited to discuss which steps should be made to further enhance a building compliant with TEK-10 towards the nZEB target. Next, another important elaboration presented in this section is an investigation on the interaction between the building and renewable energy production systems. As on site energy production is seen as a part of the nZEB and ZEB concepts, full utilization of renewable energy sources (RES) is of extra interest. Sensitivity analysis can be a useful tool to optimize this as well.

5.1 REFERENCE CASE: OSLO'S TYPICAL METEOROLOGICAL YEAR

For the Oslo TMY dataset, the most comprehensive analysis is performed, especially concerning PV load-matching and total energy use. The sensitivity analysis presented will serve as a baseline for comparison with both the regional variations and future climate projection scenarios.

5.1.1 Sensitivity analysis using SRC

Figure 10 shows results from the performed GSA using the SRC sensitivity indices sorted after absolute value of the impact. The GSA is run for a typical metrological year in Oslo. This figure will serve as baseline for the remaining climatic scenarios to illustrate differences in the outcome of the simulations.

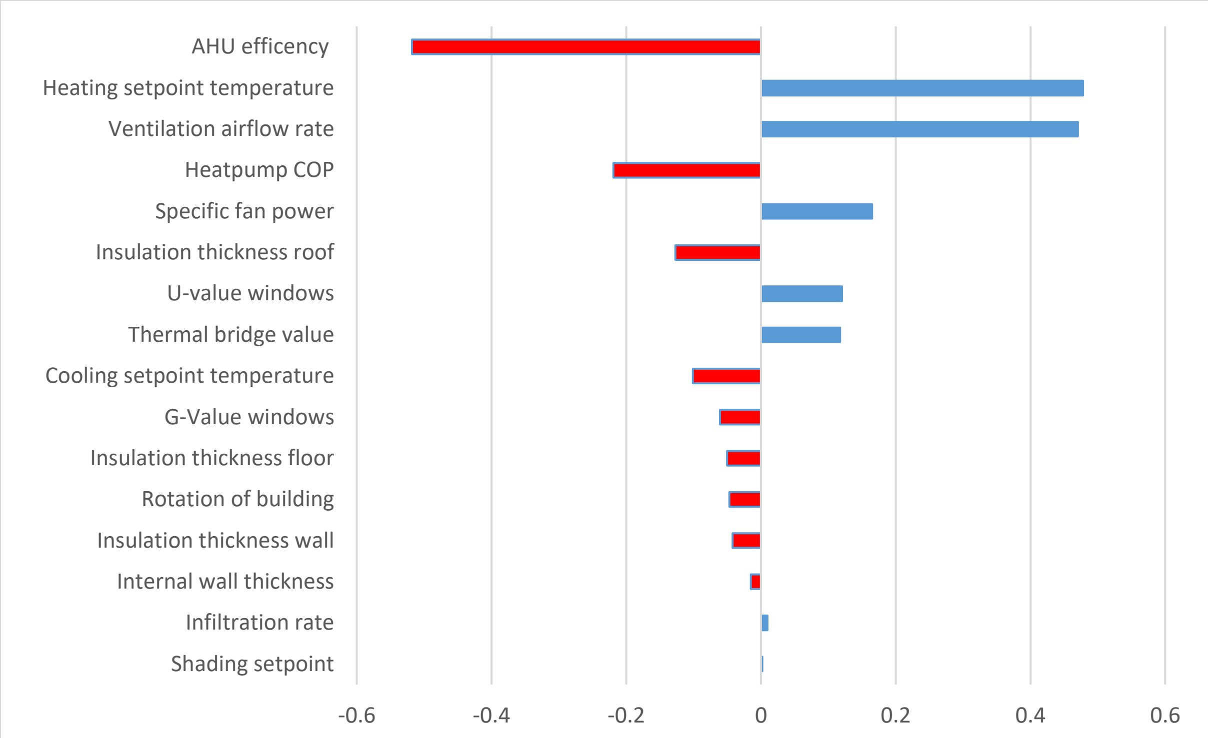

Figure 10: SRC for TMY in Oslo on energy use for space heating, cooling and auxiliary systems

5.1.2 Energy system's parameters

The outcome of the sensitivity analysis depicted in Figure 10 presents a few important findings. First, the most important factors that affect the energy use for space heating, cooling, and auxiliary energy for pumping and ventilation are the *air handling unit efficiency*, the *heating set point temperature*, the *ventilation airflow rate*, the *heat pump efficiency* and the *specific fan power* of the fans mounted into the air handling unit. All these factors concern the energy system side of the building. The first building envelope's factor is the *insulation thickness of the roof*, and is the fifth factor, with substantially lower impact than the four above it. This seems to suggest that the focus for energy savings in high performance buildings, where the building envelope is already well optimized, should be in optimization of the building conditioning systems.

Looking at the two factors *ventilation airflow rate* and *internal set-point temperature*, they are both governed by indoor comfort, which means that they cannot be changed without accounting for the user demands into the building. A conclusion is that an effort concerning demand controlled ventilation and heating, and increased focus on the system side of a building should be prioritized with respect to continuing increasing the performance of the building envelope for high-performance buildings compliant with TEK-10.

5.1.3 Infiltration rate

The most unexpected finding in the sensitivity analysis was the low impact of the infiltration rate. This called for an extra investigation. In literature, a comparable investigation have been perform by Tian et al. [63], with a bit different approach. Tian et al. investigated the impact of input variables on carbon emissions. This is somewhat comparable to energy used for space heating and cooling because of the relationship between delivered energy and carbon emissions. In Tian et al.'s research, it was found that infiltration rate is the most important factor on carbon emissions in a UK climatic scenario. Even though the climate and the building model is somewhat in line with this research, the infiltration rate investigated were between 0.15-0.4 ACH at atmospheric pressure. Applying a conversion factor of 20, as suggested by Sherman et al.[64], the range is between 3-8 ACH at 50 Pa.

This shows that a dwelling is highly sensitive to infiltration at these rates. The same findings can be seen by Hopfe [38], where infiltration rate with expected value of 0.5 and standard deviation of 0.17 in atmospheric pressure (*μ=10*,σ=3.4 at 50 Pa) is investigated. Also for this publication infiltration rates proved to be most the most sensitive input.

In this research, the infiltration rate is in compliance with TEK-10 at 0.6 ACH at 50 Pa, with a 10% standard deviation to represent epistemic uncertainty. The research by Hopfe and Tian does not undermine the results in this thesis, due to the different infiltration rates investigated.

The results from this investigation can question if further improvement to air tightness is necessary for the standards. Looking at the results from Hopfe and Tian it is clear that improvements from high infiltration to low infiltration is beneficial, but further improvements might not be.

5.1.4 Building envelope's parameters

The three building envelope factors that impact energy consumption the most are the *insulation thickness of the roof*, *U-value of the windows* and *thermal bridges*. Again, these impacts must be seen considering the expected values, and should not be interpret without looking at the building model. The building envelope's impacts are behaving somewhat as expected, since envelope parameter like insulation thickness is easier to improve than system parameters, a great deal of improvements have already been implemented by the standards.

Comparing the typical requirements the requirements of the passive house standard (NS3701 [65]) with those of the TEK-10 standard (NS3031 [1]), there is a significant focus on improving the building envelope parameters. Looking at the results of the GSA, one might think that this would be a misguided focus, since the building envelope is not the most sensitive input. However, the passive house standard sets a strict limitation to energy use, and achieving them requires implementation of strategies like demand controlled ventilation, passive ventilation and utilization of solar thermal energy. Focusing on the more sensitive inputs found in this project.

5.1.5 Histogram of specific delivered energy

To get a better overview of the spread in the output of the model, the output is presented as a specific delivered energy, that is the yearly delivered energy normalized over the net floor area (in kWh/m^2).

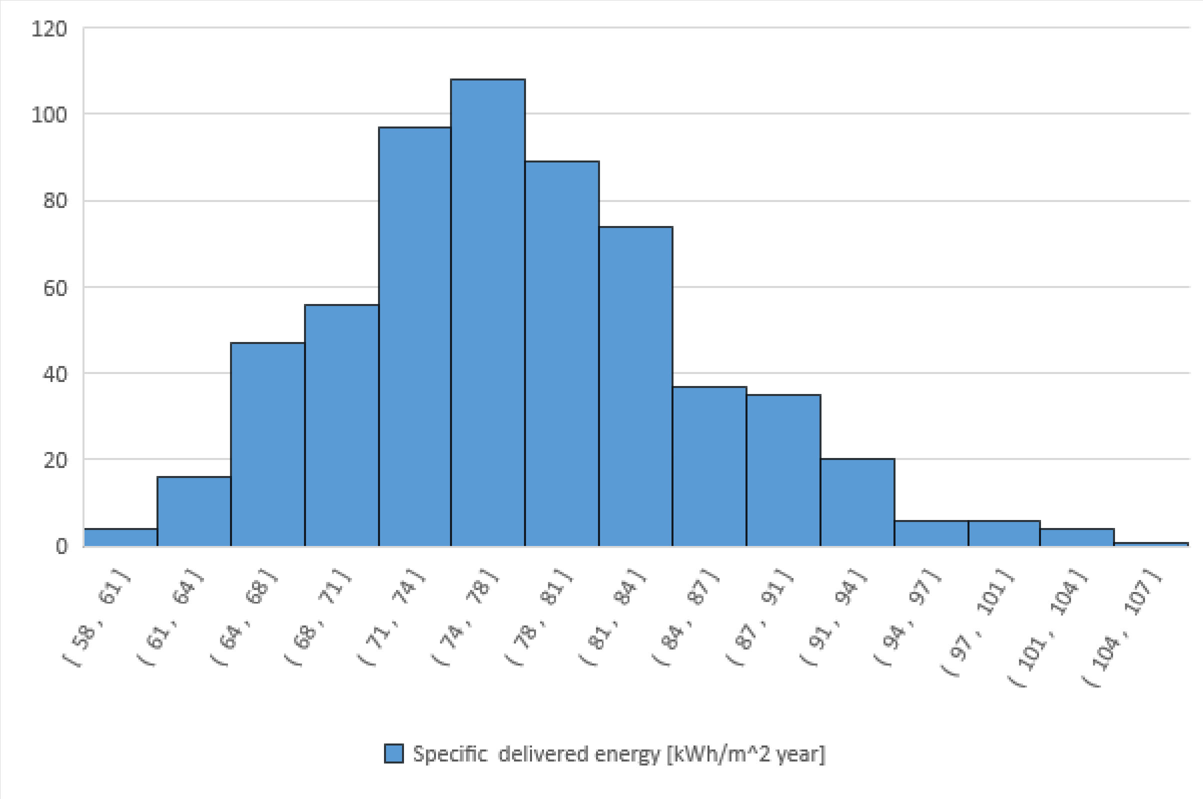

Figure 11 – Specific delivered energy for Oslo typical meteorological year per net floor area

As we can see in Figure 11, there is a high spread between the maximum and minimum values and the minimum value is only 55% percent of the maximum one. Other than that, the distribution of output data is as expected. Keeping in mind that several of the cases will fall outside the TEK-10 standard, since expected values of input are slightly lower that the minimum requirements, all of the models are far below the average energy use of kindergarten and schools in Norway that is about 160 kWh/(m^2 a) [66]. What is interesting is that one of the 600 simulated cases obtained the minimum value of the specific delivered energy for passive house according to NS3701,at less than 58.7 kWh/(m^2 a) [65].

5.1.6 Selected input values and energy use from sorted data

From the histogram, we can identify several interesting aspects of the specific delivered energy for the case of TMY in Oslo. To further elaborate, a selection of cases will be presented. The cases are: the minimum, the maximum, the first and third quartiles and the 5^{th} and 95^{th} percentiles.

Table 6 – Total delivered energy use for the case at first, second, third quartiles, 5^{th}, 95^{th} percentiles, minimum and maximum

	Min	5%	Q1[25%]	Q2[Median]	Q3[75%]	95%	max
Simulation number	547	423	582	376	568	519	442
delivered energy [kWh/(m^2 a)]	57.7	65.3	71.9	76.6	82.3	92.0	104.2

Table 6 is displaying the total delivered specific energy and the simulation of which provided the results. Between the first and third quartiles 50% of the data points can be found. This means that half of the simulated cases have an outcome varying with only 10.4 kWh/(m^2 a). This together with the impacts from the SRC can tell us that a small number of extreme cases represent most of the spread in the data and that the energy concept represented by TEK-10 is quite robust with respect to specification uncertainties.

In Table 7 reported in the appendix, the input values from each of the cases of Table 6 are presented. From this table, we can see that input values with a high SRC tend to change systematically. For example, the heating set point temperature is higher for cases with high energy use. For inputs with lower SRC the behavior is less bias, like the building rotation. This is as expected, and the SRC is a better representation for input importance. What is also interesting is the minimum and maximum values for some of the inputs. Looking at the air handling unit efficiency, the maximum energy use has an efficiency of 0.586, while the minimum is at 0.803. Both these values are within realistic values, depending on how the system is designed or operated. What we can derive from this is that both these cases are plausible, and choosing one instead of the other can greatly reduce the energy consumption of the building.

Another aspect of Table 7, is that even though the cases that implement the minimum and maximum values from the distribution for the input variables tend to have values of the consumptions in the tails of the consumption distribution, implying that the optimal energy performance is not achievable simply assembling the optimal individual components. By this we mean there is room for further improvements within the selected distributions, since this only represent the minimum value for semi-random selection of input values.

5.1.7 Assessing the validity of the data

A key factor in GSA is the selection of the input variable distributions. In this analysis, we have chosen the variables attempting a systematic change in each input. From the literature review we have found that a common approach to GSA is to combine it with an uncertainty analysis and select input distribution with individual consideration. De Wild et al. [35] used the same 10% standard deviation approach as done in this project for most variables, but used a 50% standard deviation for infiltration rate and metabolic rate. Mara et al. [40] describes their inputs as: “uniformly distributed over a generous uncertainty range proposed by one of the authors” [40]. Looking at the data, their input accounts for a large problem space, and is suitable for their project. A critique of this systematic method is that it does not offer a realistic approach with regards to what is possible and what is not. An example is that a 10% change in either insulation thickness or infiltration rate would seem trivial and of little extra effort, while improving the performance of and air handling unit with 10% could be completely un-realistic.

The systematic approach is also chosen for this project. It is limited by the same problems with changes not being in line with what is realistic. However, it also supports the notion that input factor distribution must be in relation to the research question, and the validity of the research is limited by the choice of input distributions. In other words, the outcome of this project should only be used as design support for similar buildings and input distributions must be individually evaluated.

5.2 IMPACT OF CLIMATE CHANGE ON THE BUILDING DESIGN

For investigation of the impact of climate change on building design, it is of interest to compare the results of the GSA for the four different weather scenarios created upon the TMY of Oslo, as discussed in section 1.2.2. Further elaboration of the validity of the climatic files generated can be found in the discussion of Jentsch et al. [67] on CCworldWeatherGen.

In this section, the simulation and GSA outcomes for future weather scenarios are presented and discussed.

5.2.1 SRC for the TMY and future weather scenarios

The SRC for the four different climatic cases have been plotted in Figure 12, while a numerical comparison is presented in the appendix in Table 8. Keep in mind that a change in SRC for an input variable can both be explained by the variable itself, or the total change in all the other variables.

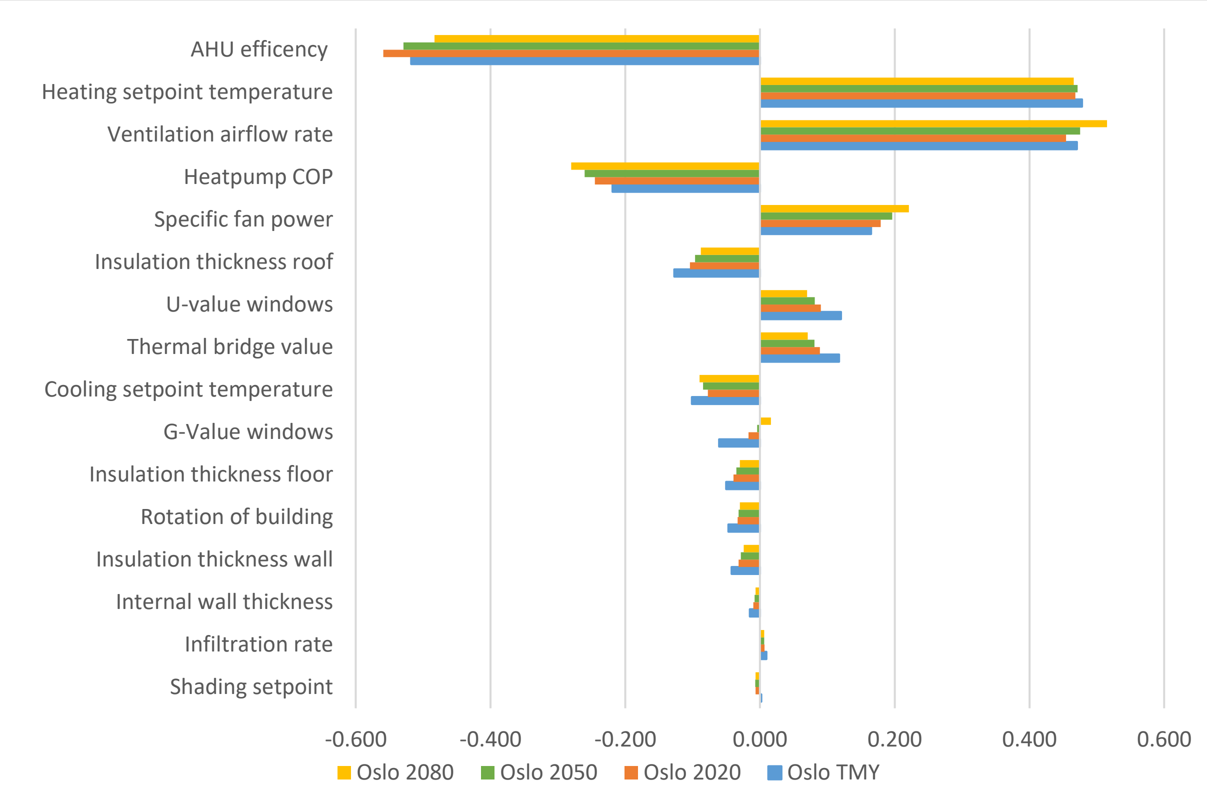

Figure 12 - SRC for typical meteorological year, 2020, 2050 and 2080 climatic files for Oslo

Figure 12 is showing a gradual change in SRC values for the selected input variables, considering that the climate is gradually changing towards a warmer weather, this is expected. What could be mentioned as a first observation is that the changes in impacts are low, compared to the changes in energy use. The total delivered energy that is dominated by energy required for space heating is reduced by 19%, 25% and 29% for 2020, 2050 and 2080 respectively.

If we look directly at the inputs concerning thermo-physical properties, like the building envelope, we can see a gradual reduction in impact. This can be explained by an increase in the outdoor temperature that leads to a reduction in energy use for space heating. This would be the case for any modeled steady state system, without cooling needs.

Two factors not behaving like expected are the specific fan power and heat pump COP. Intuitively one could expect the COP to reduce in impact when the temperature is increasing, but this is not the case. If the cooling demand would increase, the COP would also increase in impact, but the cooling set point temperature explain only a limited change in the total delivered energy of the building due to its smaller share with respect to space heating. What can explain the behavior, is changes in other variables. Based on the calculation method of SRC if a variable decreases in impact, the rest of the variables will increase. This is a limitation of the method applied here, but it does not void the results.

Glazing g-values behaves interestingly by reducing energy use in the Oslo TMY, and increasing energy use in 2080. In this model, the g-value describes solar energy transmittance of glass, accounting for the fraction of solar radiation that actually enters a building through the glassing, both direct and diffuse radiation. For the TMY case, this energy is contributing to heating and hence reduces the building's heating demand. For the 2080 case, this energy is contributing to overheating in the indoor built environment and increases the building's cooling demand.

This model also implements an effective solar shading strategy. If this was not the case, overheating could be a big issue, especially in the 2080 case. Because of this effective solar shading, the impact of window g-values are expected to have low impact in the overall energy use of the building compared to a model without solar shading.

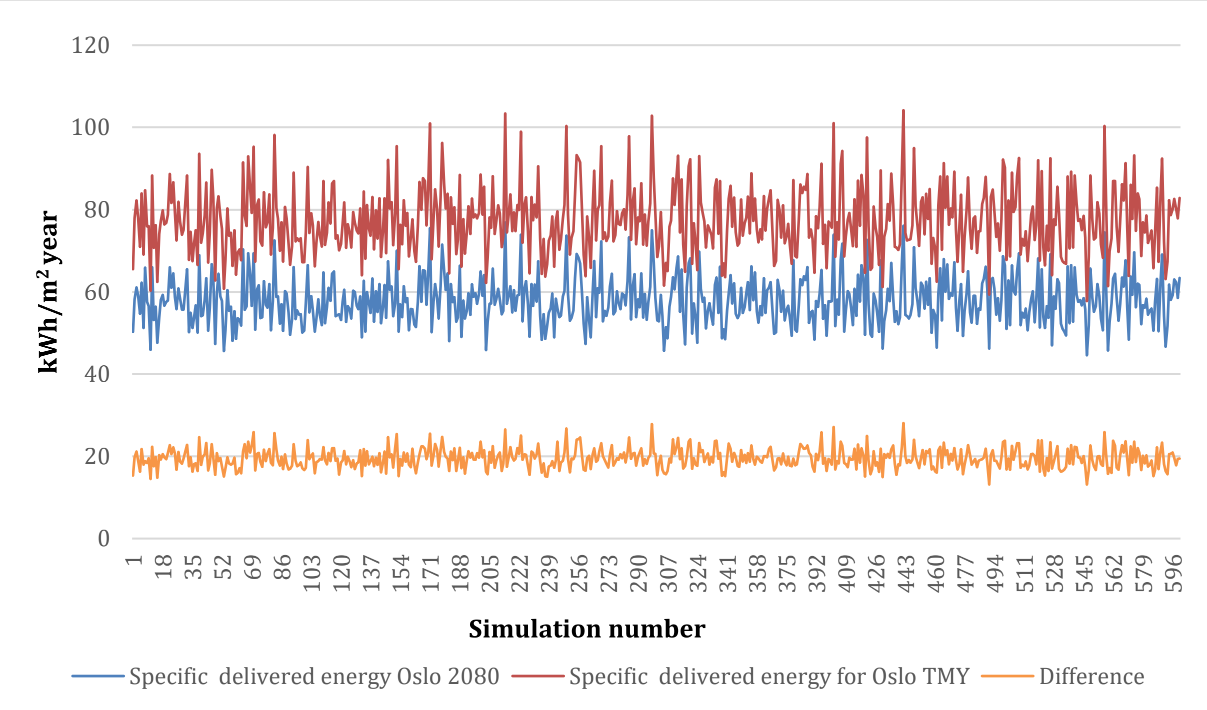

Figure 13 -Total delivered specific energy of Oslo 2080 and typical meteorological yea.

Figure 13 show the predicted energy demand for the different models in both present and future weather scenarios (2080). There is a significant difference, varying slightly from model to model.

5.2.2 Implications

As mentioned, the energy demand of the building will see a substantial decrease with time, with a reduction of energy for conditioning the building at 29% in 2080. The question of if we should design a building for the present climate, or the average situation over the lifetime of the building has surfaced. From the data collect, we can see that even though there is an expected change in impact, based on difference in temperature inside and outside the zones, the change is not particularly big. This implies that the same efforts for energy reduction applied today will be valid in the expected future projections. Even though there is a significant reduction in energy demand, the design variables to focus on for further improvements, starting from the TEK-10 baseline, are not changing over the time due to climate change. Therefore, in terms of building's energy performance, TEK-10 offers a robust design guideline for the present, as well as the future. Again, this analysis is only valid for the TEK-10 specifications of which this building is modeled.

5.3 DIFFERENT CLIMATIC ZONE: BERGEN TMY

With regards to the discussion on the effect of different climate zones, a simulation was done with the Bergen's TMY weather file. In this section, we will investigate the implication of the difference between the SRC of this file and the Oslo TMY file.

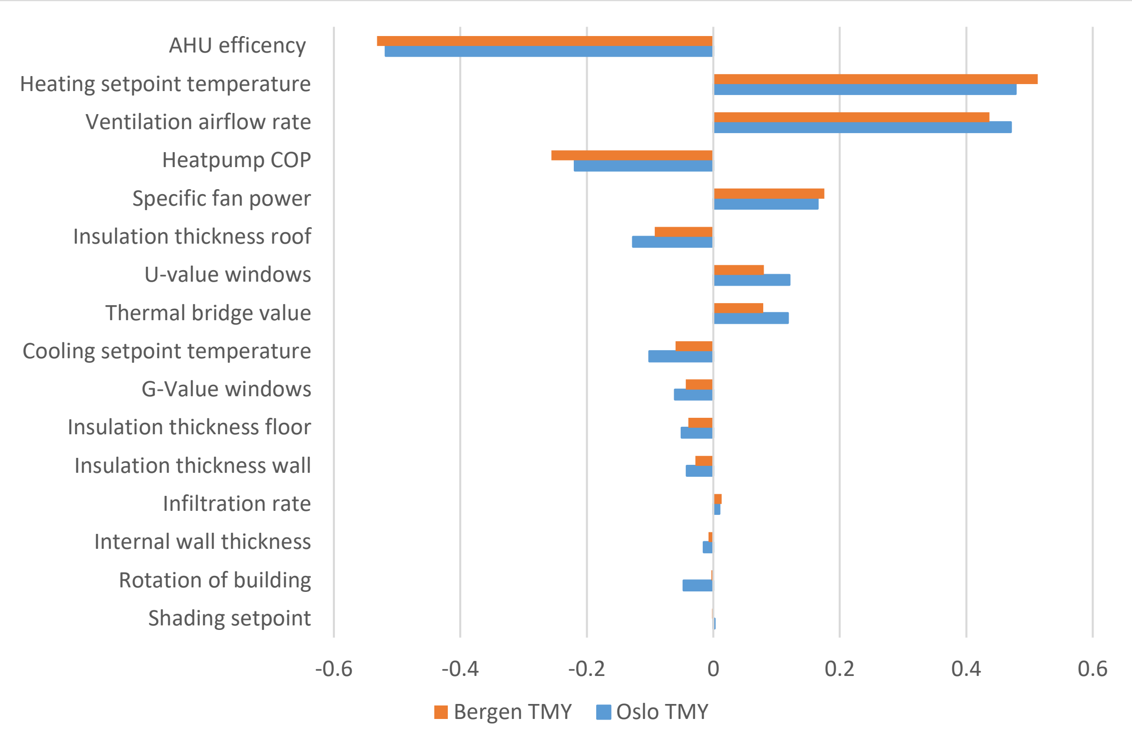

Figure 14 - SRC for Bergen TMY and Oslo TMY

In Figure 14, the SRCs of the Bergen TMY and Oslo TMY are compared in the same manner as already done for the future weather scenarios. This graphs highlights those input variables related to temperature difference. There is a drop in SRC for thermal bridges, insulation thickness, U-value and ventilation airflow rate. This tells us that a building in Bergen needs less energy for space heating compared to Oslo. If we are looking at the yearly average temperatures for Bergen and Oslo they are 7,8 °C and 5,9 °C, respectively. Adding to this, the degree-days are 2850 °Cd for Bergen and 3778 °Cd for Oslo [50]. We can see a significant higher demand for heating in Oslo, explaining the difference in SRC shown in Figure 14. Rotation of the building also has a notable change in impact. The explanation for this should also be found in the weather file and is probably due to a lower solar radiation, because of cloudier weather in Bergen.

After stating that the difference in SRC for Oslo and Bergen are behaving like expected, we can discuss the robustness of TEK-10 design as a representative for a divers climate zones. First, even though the changes are behaving as expected, the impacts are not changing in a large scale. If we again look at Table 8 in the appendix, the percentage change for each variable, especially the most influential ones is in the order of 3 to 7%. The parameters of the building envelope have a change between 22-41%, illustrating that the variations in the building envelope explain lesser the variation of the delivered energy for space heating and cooling, and production of DHW in Bergen than in Oslo.

All in all, different local climates are important for energy use for heating and cooling in buildings, as we see a 25% reduction from Oslo to Bergen, correspondent to a similar difference in the degree-days. Moreover, the SRC values and rankings of the input variables are similar. This tells us that the TEK-10 design appears to be robust for two different climatic zones as well. Improvements in the standard will have a similar impact for the two scenarios, especially on the system side of the building.

5.4 TOWARDS NZEB

In this section, there will be a discussion on the TEK-10 standard in regards to the concepts nearly Zero Energy Building (nZEB) [56] and Zero Emission Buildings (ZEB) [68]. Based on the findings in section 5.1, we want to discuss how to best approach these two different ZEB concepts starting from a TEK-10 compliant building model. To do this, some sort of energy generation must be applied to the building. For the simulation performed, a PV-system as described in section 4.3.2 **Feil! Fant ikke referansekilden.** is evaluated.

For the concept of ZEB depending on which definition you choose, the energy use and energy production should be equal over a given time period. This does not account for how the energy is used, and assumes that exported energy to the grid is of equal value as the energy used for the building. As this is not the case from an economical perspective, we wish to investigate how to maximize the on-site utilization of energy production. GSA is a good tool for this evaluation, and an extensive analysis of how much renewable energy generated locally is actually used by the building using the so-called load-matching index [57].

5.4.1 Achieving the zero energy/emission target starting from TEK-10

The building model is a rectangular on construction with a flat roof over one floor, not included the unheated basement. Therefore, there is a large area suitable for the installation of a PV system. It is assumed no shading of the PV cells, since we don't have a specific location for the building, so the results will overestimates the figure we might have in a real building. We can now calculate the size of a PV-system required to achieve the net Zero emission balance throughout the reference year for the Oslo TMY for the building case representing the median of the energy use from Table 6 that is at 76,6 kWh/m^2. For this case, to achieve the net zero delivered energy, we need 386 m^2 of south facing PV panels at 45° angle.

The approach to nZEB concepts of applying sufficient amount of energy generation to account for uses is not necessarily the best. In this model, there is a lot of available space for mounting of PV-systems, and from a theoretical perspective, it might seem like a good idea. However, reducing energy consumption is often a far better approach to achieve an nZEB target, and is the key motivation for running the GSA in the first place. If we calculate the required PV-area for achieving net zero energy for the minimum energy use case for the TMY Oslo model, it comes to about 290 m^2. Now it is possible to evaluate the cost of reducing the size of the PV-system and the cost of reducing the energy consumption for the different building models.

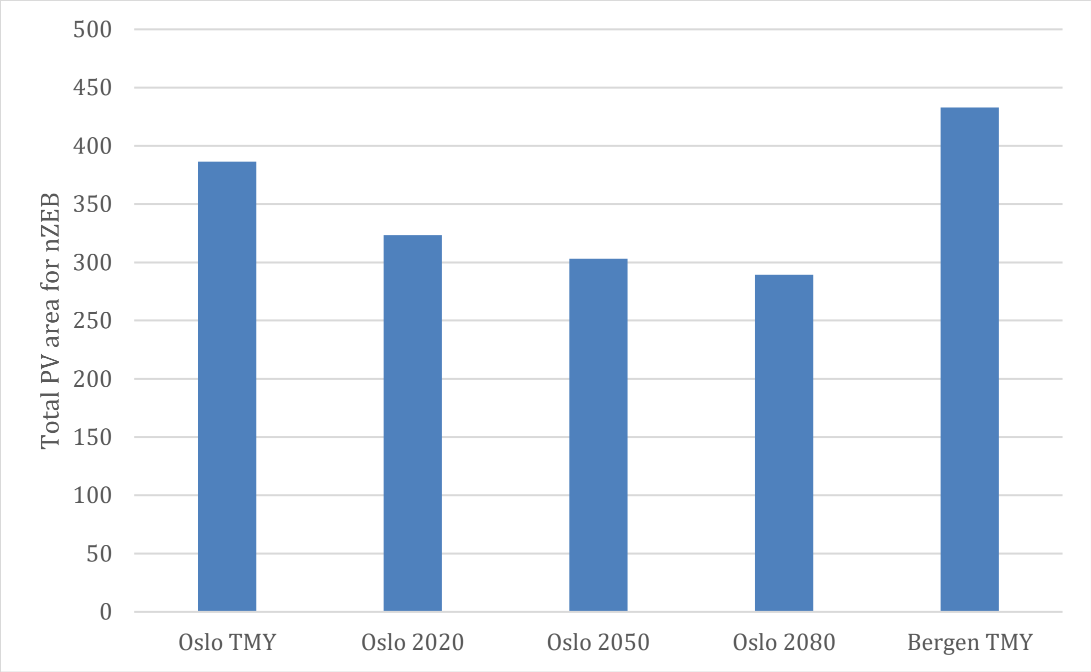

Figure 15 - Total PV area for the median energy use case of each weather scenario

To further elaborate the requirements on the PV-systems for reaching ZEB targets Figure 15 presents the total PV-area needed to reach net zero energy throughout a year. Notice that Bergen has a substantially higher PV-need, while still using less energy. This is because the weather file offers a lower PV-production throughout a year.

Another interesting finding from the simulation data is that we will see a substantial reduction in energy use in the future weather scenarios, mainly due to a reduction in the heating demand. For the case of ZEB evaluations, one could include these energy forecasts in the calculation, to reduce the required energy generation. If the lifetime of the building is assessed, the building can be design for under production in the first years, and overproduction in the later years of the lifetime (assuming constant the efficiency of the PV system).

To concluded this evaluation, we can state that the TEK-10 energy design is compatible with concepts of ZEB and nZEB if a substantial area is available for the installation of the PV modules, but reduction of energy use might still be easier than increasing energy generation. However, at one point it will be more economical to increase generation, rather than to reduce consumption, and the GSA could support this this evaluation.

5.4.2 Load-matching

After discussing net zero energy, it is of interest to investigate how much of this energy is exported to the grid, and how much is used for the building. To evaluate this, the load-matching index is used. In this section, we will first discuss how the time resolution of the evaluation impact the results, followed by a presentation of the simulation data from the 600 cases using the Oslo TMY. Finally, we will use the Load-matching index in a GSA to investigate how to design for maximizing the utilization of on-site electricity generation.

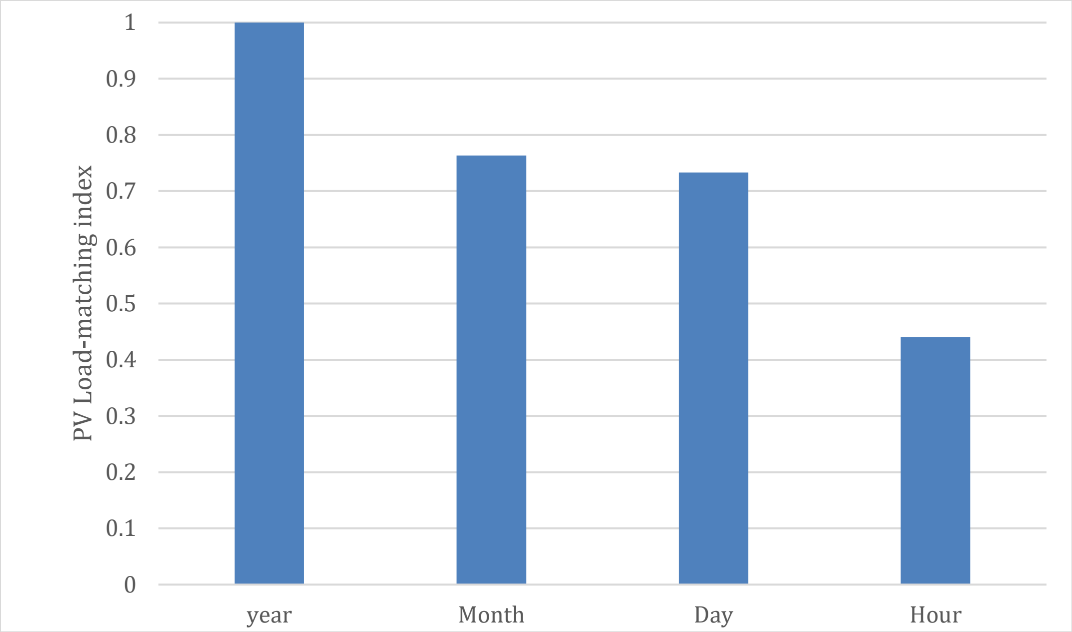

Figure 16 - Load matching index with different time resolution

Using different time resolutions for Load-matching indexes can be beneficial depending on what information is of interest. In the previous section, a yearly approach was used to investigate if the annual energy generation exceeded the annual energy consumption. This approach is highly depended on grid interaction, and often assumes that the value of exported energy is equal to imported energy. In Figure 16, the Load-matching index for simulation number 417, representing the median load match, is presented with different time resolutions. This figure highlights a few interesting notions.

First, according to the calculation with the hourly resolution, most of the energy generated is exported (LMI = 0,44). This is because energy use and energy production do not coincide on an hourly basis. Since the building investigated is a kindergarten, a higher load-matching is expected due to a better match between production and use. Still the building does not achieve more than 44% load-match. Other buildings, like residential housing could expect a lower matching, while a facility for freezing or cooling could expect a high degree of load-matching.

If we now look at the daily resolution for the load-matching index, we can see a substantial improvement. This indicates that the mismatch between energy required by the building and the energy produced is closer if assessed on daily basis, than it is on an hourly basis. Furthermore, it could imply that short-term storage solutions like battery packs could greatly reduce the dependency on the energy grid for this specific building.

Moving on to a monthly resolution, there is almost no increase in performance. While annual resolution offers full load-matching. This tells us that after accounting for daily fluctuation, most of the remaining difference comes from seasonal difference. Short term energy storage is not suitable for accounting for seasonal change, and some degree of grid interaction should be expected for all the ZEB and nZEB concepts.

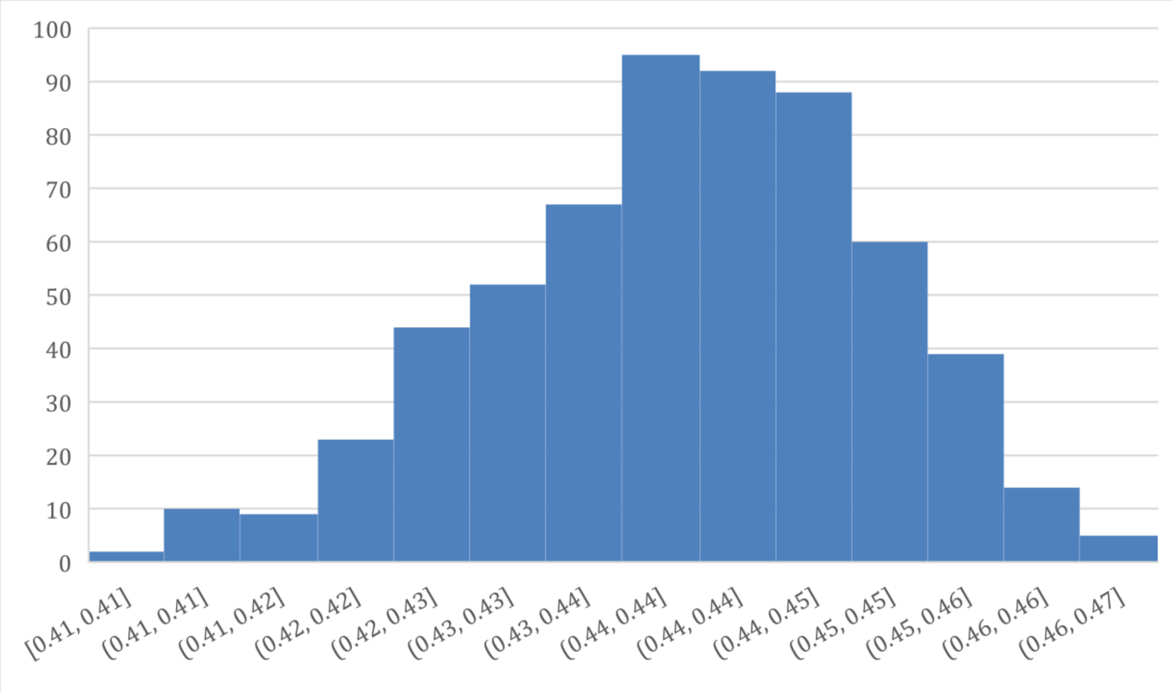

Figure 17 - PV Load-matching index histogram for TMY Oslo

In Figure 17, the load-matching index for all the TMY Oslo simulations are presented with an hourly time resolution. From this figure, we can see that there is a small spread in the data, ranging from 41% to 47% of the load-matching index. It may be of interest to further elaborate on what impacts the load-matching. To do this, a GSA with the same input variables as the one for energy use has been performed for the scenario Oslo TMY.

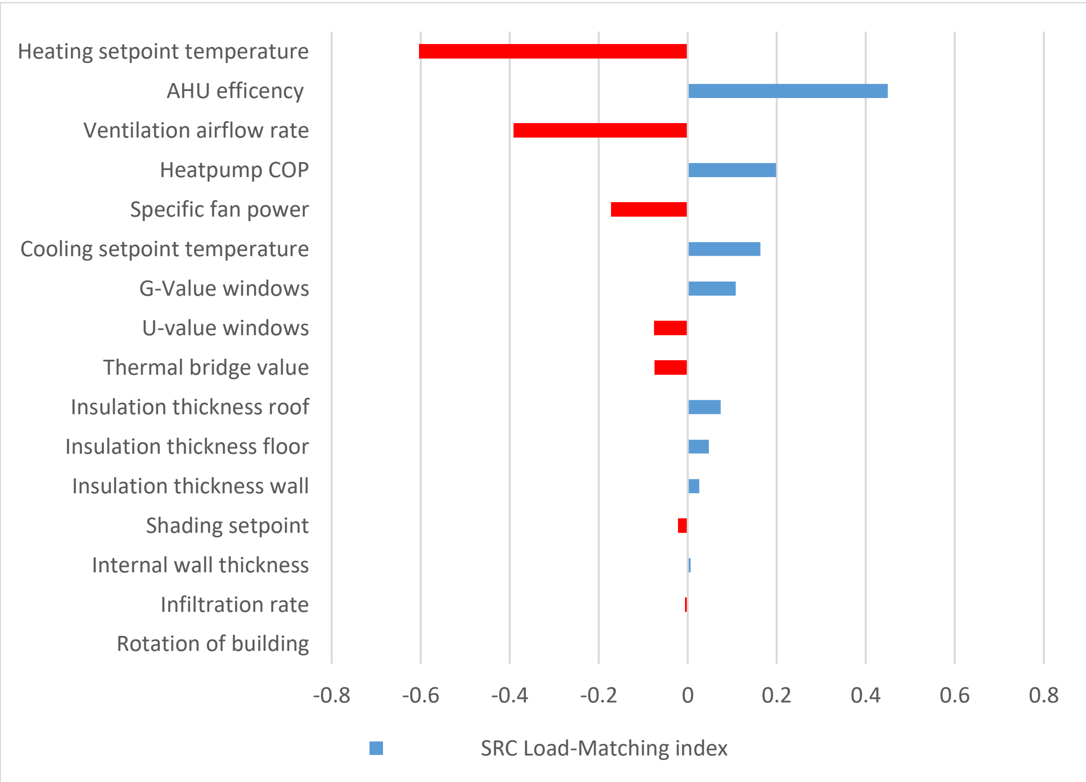

Figure 18 - SRC for Load-matching Index on the case of typical meteorological year in Oslo

Looking at Figure 18, we can see how the selected input variables impact the load-matching index. Starting from the top, the energy system side of the building is dominating the GSA for the load-matching index. The building envelope parameters have a small but positive effect, hence increasing insulation thickness and reducing U-values will increase the load-matching.

Comparing the load-matching index SRC to the delivered energy SRC we find similarities suggesting a high correlation between the two.

5.5 IN RELATION TO OTHER PUBLICATIONS

Comparing directly the outcome of the GSA to another project is challenging and not necessarily fruitful. This because the outcome is strictly dependent on the model. A highly insulated building, using active systems, will be dependent on the active systems, as this analysis shows. However, a similar building envelope, utilizing passive strategies, like natural ventilation, might show a different result.

In general comparison we can see that infiltration rate tends to be of greater importance in other works like in Tian et al. [39], Hopfe [10], Mauro [43] and Cemesova [69], even though their results are varying based on the model in question. The argument explaining the low impact of infiltration rate in this study is that the investigated range of infiltration rates are significantly lower than the publication mentioned above. This is further elaborated in 5.1.3.

Set point temperature and ventilation rate as highly important factors, seems to be in line with the findings of other publications, as Garcia [70], Brohus [71] and Lam [37]. The last one for a very different climatic scenario, but it still indicates the importance of HVAC system parameters. The most influential parameter, air handling unit heat recovery efficiency is highly correlated to the set point temperature and ventilation rate, and its impact will also be in line with the publication mentioned because of this.

Comparing the impact of climate change on the building performance on the building performance, could be a more beneficial comparison. First, several studies involving future weather data investigate the thermal comfort aspect of increased temperatures, as done by Pyke et al. [72], and Tian [39]. These studies highlight an important challenge, to provide thermal comfort in a changing environment. This was unfortunately out of the scope of this project, but the platform developed is highly suitable to further expand on this topic. The building model is based on the assumption that thermal comfort will be at a satisfying level, making the project itself unsuitable for evaluation of overheating and underheating.

Tian et al. [39] assess the change in annual heating energy, depending on the number of degree days, and finds a linear increasing relationship with an R^2 of 0.989 when analyzing future and present weather data. This is somewhat inline whit the findings for local variation between Bergen and Oslo in energy use, where difference in energy used for space heating was 25% less in Bergen with 25% fewer degree days. This could be further expanded to the decline in energy use, with the increase in the outdoor temperature in the future weather projections. The number of degree days in 2080 is calculated to 2682, 29% lower than for the case of TMY, while the energy reduction is also at 29%. This strengthen the indication that the building is operating like a steady state model.

With regards to the load-matching index the time resolution investigation outcome show the same trends as the one performed by Voss et al. [57], indicating a robustness of the method. For the load-matching sensitivity analysis, no similar studies were found.

6 CONCLUSION

In this project, a platform for performing a global sensitivity analysis on a building model using the simulation software IDA-ICE have been developed. Using the developed platform, an extensive case study on a retrofitted kindergarten has been performed. The kindergarten is based on an existing building located in Milan, Italy, where a suggested retrofit has been applied in the building model. Before the model retrofit was applied, the model was calibrated with measured data from the building itself. The energy retrofit is based on the Norwegian standard for calculation of energy performance of buildings: NS3031 [1] (TEK-10). The main findings from this case study will be presented in this section, together with suggestions for future work.

6.1 MAIN FINDINGS

The main outcome of the sensitivity for a typical meteorological year, presented in section 5.1, is the importance of HVAC systems in regard to energy use. For the fully conditioned building, envelope parameters have a significant lower influence on the overall energy consumption than parameters concerning the system side of the building. This is found to be caused the high level required for the building envelope components by the new Norwegian TEK-10. This could imply that a discussion surrounding further improvements of the building stock in Norway, by means of changing the standards, should focus more on active systems and demand controlled system than on building envelope parameters that have already been enhanced. Furthermore, the investigation highlights that small variations of the infiltration rate have a low impact on energy use for the selected sample.

On investigation of future weather data, a strong relationship between energy use and external temperature is established. In line with other research, energy use for heating will decrease in future climatic scenarios while energy need for space cooling is expected to increase, even though Oslo is and will remain a strongly heating-dominated climate. However, the sensitivity analysis shows that the same input parameters will be of importance for the energy use, so a design reducing energy in buildings today, will yield the same effect in the future. This indicates that the standard offers a robust design in terms of climate change impact on energy use.

Evaluating the standard in relationship to concepts of near zero energy buildings, we see energy generation as the means for achieving different targets. The energy related to building systems is often dependent on thermal comfort criteria's, making them undesirable to reduce. Hence integrated energy generation offers the possibility of achieving either zero emission building or near zero energy goals.

For the case of near zero energy, an evaluation of load-factor has been performed. The outcome of this investigation shows that the building will be highly dependent on grid in achieving a net ZEB target. Relatively big improvements can be achieved by short-term energy storage, compensating for daily fluctuations. However, seasonal fluctuations in energy generation cannot be compensated for, and grid interaction is necessary.

A final outcome of the project is the global sensitivity analysis of the load-factor index. This analysis shows that the same parameters for reducing energy consumption are important for increasing the load-matching index. This outcome is interesting because it establishes a high correlation between load-matching index and energy use.

6.2 FUTURE WORK

One of the main outcomes of this project is a platform for running the GSA, allowing easy adaptation for other building models. Because of this, the author sincerely hopes that this project will encourage further work. From the platform development, a few experiences should be highlighted:

- In relation to IDA-ICE, it is highly beneficial to apply parallel processing. Calculation time in the software is exceptionally long compared to other BPS software, making the bar for running a GSA higher than necessary.
- The platform uses a difference script for changing input variables. It is possible to directly change aspects of the idm-file, which can allow for easier implementation in other software like modeFrontier.

The case study offered insight in the outcome of a GSA for a high-performance building. From this analysis, there were several interesting findings. However, the findings also illustrated some weaknesses of the implementation. These should be further investigated:

- Achieving convergence for rank-regression is desirable. A theoretical relationship between number of input variables and convergence would be highly beneficial. If this is un-obtainable, an investigation like the one performed by Tian [12] on convergence should be performed for several input variables.
- Increasing the size of the sampling space could be interesting for increase the validity of the model. This, or running the same sample size for different building types would improve the understanding of energy performance of buildings.

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7 APPENDIX

Table 7 - Selected cases and their input values for TMY Oslo

	Min	5%	25%	Median	75%	95%	max
Insulation thickness wall [m]	0.141	0.160 5	0.152	0.137	0.171	0.144	0.155
Insulation thickness roof [m]	0.294	0.273	0.254	0.287	0.237	0.193	0.240
Insulation thickness floor [m]	0.374	0. 398	0.409	0.354	0.369	0.331	0.330
Ventilation airflow rate [m^3/m^2h]	6.42	7.354	7.056	7.045	8.172	8.30	8.4
G-Value windows [adimensional]	0.468	0.381	0.372	0.378	0.454	0.363	0.3947
U-value windows [W/m^2K]	0.670	0.540	0.657	0.603	0.645	0.557	0.565
AHU efficiency	0.803	0.782	0.751	0.739	0.7256	0.695	0.586
Infiltration rate [ACH]	0.612	0.521	0.623	0.576	0.5889	0.5830	0.672
Cooling set point temperature [C°]	25.97	24.47	24.95	24.79	25.49	24.28	24.56
Heating set point temperature [C°]	21.20	21.31	21.691	22.91	22.84	22.36	22.86
Rotation of building [°]	144	114	141	110	185	164	133
Specific fan power [SFP]	2.03	2.17	2.09	2.08	2.21	2.20	1.68
Thermal bridge value [$W/K*m^2$ floor]	0.0745	0.083	0.058	0.059	0.0686	0.0102	0.0617
Shading Set Point [W/m^2]	100.88	108.9 4	84.66	104.36	112.71	91.49	108.0
Internal wall thickness [m]	0.156	0.13	0.141	0.166	0.1337	0.181	0.135
Heat pump COP [kw /kw]	4.15	4.18	3.345	4.08	4.71	3.56	3.19

Table 8 - Change in SRC and delivered energy for different climatic scenarios

	SRC Oslo TMY	SRC Oslo 2020	Change in %	SRC Oslo 2050	Change in %	SRC Oslo 2080	Change in %	SRC Bergen TMY	Change in %
Median Energy for heating, cooling, DHW and AUX	62491	50412	19 %	46618	25 %	44100	29 %	46852.6	25 %
AHU efficiency	-0.518	-0.559	8 %	-0.529	2 %	-0.483	7 %	-0.532	3 %
Heating setpoint temperature	0.478	0.468	2 %	0.472	1 %	0.466	3 %	0.513	7 %
Ventilation airflow rate	0.471	0.454	3 %	0.475	1 %	0.515	9 %	0.437	7 %
Heat pump COP	-0.219	-0.245	12 %	-0.260	19 %	-0.280	28 %	-0.256	17 %
Specific fan power	0.165	0.179	9 %	0.196	19 %	0.221	34 %	0.176	6 %
Insulation thickness roof	-0.127	-0.104	18 %	-0.096	24 %	-0.088	31 %	-0.093	27 %
U-value windows	0.121	0.090	25 %	0.081	32 %	0.070	42 %	0.080	34 %
Thermal bridge value	0.118	0.089	24 %	0.081	31 %	0.071	40 %	0.079	33 %
Cooling setpoint temperature	-0.101	-0.077	24 %	-0.085	16 %	-0.090	11 %	-0.060	41 %
G-Value windows	-0.061	-0.017	72 %	-0.004	94 %	0.016	127 %	-0.043	29 %
Insulation thickness floor	-0.050	-0.039	22 %	-0.035	30 %	-0.030	41 %	-0.039	22 %
Rotation of building	-0.047	-0.033	30 %	-0.032	32 %	-0.030	36 %	-0.003	93 %
Insulation thickness wall	-0.042	-0.032	24 %	-0.028	33 %	-0.024	43 %	-0.028	33 %
Internal wall thickness	-0.015	-0.010	35 %	-0.008	47 %	-0.006	58 %	-0.007	50 %
Infiltration rate	0.010	0.007	31 %	0.006	34 %	0.006	33 %	0.013	38 %
Shading setpoint	0.002	-0.006	423 %	-0.007	456 %	-0.006	426 %	-0.002	196 %