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Guidelines for selecting the ‘fit-for-purpose’ model complexity regarding building energy performance prediction

van Enk, E.E.E.

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Guidelines for selecting the ‘fit-for-purpose’ model complexity regarding building energy performance prediction

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Guidelines for selecting the fit-for-purpose model complexity regarding building energy performance prediction

Eindhoven, February 2016

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ABSTRACT

Building simulation software enable designers and engineers to predict the performance of buildings. Such tools have an important role in the design phase, as they help users to optimize the building envelope, and to select, and size HVAC systems, among others. However, selecting the most appropriate simulation tool is a challenge due to the large variety of choices and simulation approaches. The simulation approaches vary (complexity-wise) from spreadsheet tools to detailed building energy simulation tools, and (integration-wise) from tools that handle a single aspect of the building design, to tools that integrate multiple variables of the design process. More complex models are likely to give a more realistic representation of the physical reality, but at the meantime they require a larger number of inputs, which might not always be known or defined. This fact introduces input uncertainties. In the selection of the fit-for-purpose model complexity, the user should take into account the trade-off between abstraction modelling error and input uncertainty, so that the overall error in the prediction is minimized.

This study presents a methodology for selecting the fit-for-purpose model complexity. A new method to quantify the modelling abstraction error is proposed in order to identify this trade-off point. Uncertainty and sensitivity analyses are used as tools to contribute to the process of selecting the fit-for-purpose model complexity.

The methodology is applied on a Dutch office building and provides decision support for selecting the appropriate level of model complexity. Four levels of complexity are used within this project. The selected levels of complexity can be described as: (i) key figures, (ii) quasi steady-state method, (iii) dynamic building energy simulation using a decoupled approach, and (iv) dynamic building energy simulation using coupled modelling approach. The results show that the simple quasi-steady state method tool can provide guidance for selection among two competing building design solutions in an early design stage. The two designs differ from each other with respect to glass type, window surface area, and the resistance of the thermal envelope. However, the simple tool is unable to provide decision support for selection among HVAC systems and sizing their equipment. The comparison of two coupling methods results, decoupled and fully integrated, give some reason to assume that the use of the fully coupled approach is not necessary for the investigated case study, given the fact that both modelling approaches are equivalent from the perspective of decision making. In addition, the monthly profiles are comparable and the yearly results and peak loads remained within 20%. We limit the investigation to a Dutch office building with CAV system, and focus mainly on energy consumption outcomes.
Samenvatting
SAMENVATTING

Gebouwsimulatie wordt gebruikt om de prestaties van gebouwen te voorspellen. Die simulatietools hebben een belangrijke rol in het ontwerp proces, zij kunnen worden gebruikt voor o.a. de optimalisatie van de gebouwschil, de keuze van het HVAC-installatie en het dimensioneren van de systemen. De keuze van het meest geschikte programma is een uitdaging, gezien de grote variëteit aan simulatieprogramma’s. De aanpak van simulatieprogramma’s kunnen worden ingedeeld naar oplopende complexiteit. Van enerzijds simpele rekensheet tot anderzijds gedetailleerde energieprogramma’s. Van tools, die een enkel aspect van het gebouw bekijken tot tools die meerdere aspecten van het ontwerpproces integreren. Complexere modellen zullen waarschijnlijk een meer realistische weergave van de fysische werkelijkheid geven. Ondertussen vereisen zij een grote hoeveelheid invoerparameters, die niet altijd beschikbaar of al gedefinieerd zijn. De aannames die bij de invoer worden gedaan brengen onzekerheden bij de invoer met zich mee. Bij de keuze van de ‘fit-for-purpose’ modelcomplexiteit moet de gebruiker rekening houden met de wisselwerking tussen het abstractieniveau van een model en de invoer onzekerheid. Om de onzekerheid in de gehele modelvoorspelling te minimaliseren moet getracht worden deze wisselwerking te identificeren.

Deze studie presenteert een methode voor het selecteren van de ‘fit-for-purpose’ model complexiteit. Er is een nieuwe methode voorgesteld om de abstractie in de model te kwantificeren, zodat het kruispunt tussen de modelleringsfout en de invoer onzekerheid kan worden bepaald. Onzekerheid-en gevoeligheid analyses dragen bij aan het proces van het selecteren van de ‘fit-for-purpose’ modelcomplexiteit.

De methode wordt toegepast op een Nederlands kantoorgebouw en biedt ondersteuning voor het vinden van de ‘fit-for-purpose’ model complexiteit. Vier levels naar oplopende modelcomplexiteit zijn geselecteerd, te weten: (i) vuistregels, (ii) quasi steady-state tool, (iii) dynamische gebouwsimulatie met een stapsgewijze aanpak, en (iv) een dynamische gebouwgebouwsimulatie met een gekoppelde aanpak. De resultaten tonen aan dat de quasi-steady state tool als leidraad kan dienen voor de keuze van de meest energiezuinigste ontwerpoplossing voor het gebouwontwerp. Daar staat tegenover dat voor de ondersteuning van de keuze van de HVAC-installatie en het dimensioneren van de gebouwinstallaties is de geselecteerde simpele tool niet geschikt. De vergelijking tussen twee simulatiestrategieën, een ontkoppeldelde en een volledig gekoppelde tool, geven reden om aan te nemen dat het gebruik van de ontkoppeldelde tool niet nodig is voor de onderzochte case study, aangezien simulatiestrategieën leiden tot dezelfde ontwerpbeslissing komen. Daarbij bleven de verschillen in piekvermogen bleven binnen de 16% en de totale jaarlijkse koelvraag binnen een range van 20%. Dit onderzoek is beperkt tot een Nederlands kantoorgebouw met CAV-systeem en is voornamelijk gericht op energieprestatie indicatoren.
# LIST OF ABBREVIATIONS

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
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<tbody>
<tr>
<td>ACH</td>
<td>Air Change per Hour</td>
</tr>
<tr>
<td>AHU</td>
<td>Air handling unit</td>
</tr>
<tr>
<td>AME</td>
<td>Abstraction modelling error</td>
</tr>
<tr>
<td>BES</td>
<td>Building Energy Simulation</td>
</tr>
<tr>
<td>BPS</td>
<td>Building Performance Simulation</td>
</tr>
<tr>
<td>CAV</td>
<td>Constant Air Volume</td>
</tr>
<tr>
<td>CSP</td>
<td>Cooling Setpoint</td>
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<tr>
<td>EPC-projects</td>
<td>Energy Performance Contracting projects</td>
</tr>
<tr>
<td>EPC</td>
<td>Energy Performance Coefficient</td>
</tr>
<tr>
<td>HVAC</td>
<td>Heating, ventilation and air-conditioning</td>
</tr>
<tr>
<td>HSP</td>
<td>Heating Setpoint</td>
</tr>
<tr>
<td>IAC</td>
<td>Indirect adiabatic cooling</td>
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<tr>
<td>Inf</td>
<td>Infiltration</td>
</tr>
<tr>
<td>PI</td>
<td>Performance Indicator</td>
</tr>
<tr>
<td>SC</td>
<td>Shading coefficient</td>
</tr>
<tr>
<td>SHGC</td>
<td>Solar heat gain coefficient</td>
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<tr>
<td>S-MEP</td>
<td>Sustainable Mechanical, Electrical and Plumbing (department at the company)</td>
</tr>
<tr>
<td>SRC</td>
<td>Standardized regression coefficient</td>
</tr>
<tr>
<td>TRNSYS</td>
<td>TRaNsient SYstem Simulation</td>
</tr>
<tr>
<td>WWR</td>
<td>Window-to-Wall Ratio</td>
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1. INTRODUCTION

1.1. MOTIVATION

The focus on sustainable and efficient energy development has been growing in the past decade. With 40% of energy consumed in buildings, the European Performance of Buildings Directive (EPBD) was introduced to improve the energy performance of the building stock. The EPBD demands European countries to reduce the energy use in new buildings. For example, the Dutch government enforced energy saving measures in new buildings by introducing the Energy Performance Coefficient (EPC), meaning that new buildings should not exceed a certain EPC-value. The maximum allowed EPC-value was strengthened regularly since this measure was introduced as early as 1995. As a result, the EPC was set to 0.4 for dwellings and 0.8 for office buildings in 2015. In the coming five years energy performance requirements for new buildings will be steadily tightened to zero-energy or nearly zero-energy buildings. The stringent energy performance regulations have made building performance simulation (BPS) an essential tool for optimizing building performance[1][2]. This resulted in a wide range of modelling approaches for building energy analysis. Those approaches vary (complexity-wise) from spreadsheet tools to detailed building energy simulation tools, and (integration-wise) from tools that handle a single aspect of the building design, to tools that integrate multiple aspects of the building design [3].

Despite the great variation in the types of tools and their usage, there is a lack of methodology, or at least detailed guidelines, for choosing the most appropriate modelling approach in a Building Performance Simulation (BPS) study. It is hard to find unbiased studies that describe how the selection process of model complexity in BPS takes place, and how the choice influences the building (system) design decisions. As a result, the choice of the best model is regarded as more of an art than a science[4].

In BPS, it is tempting to choose the most sophisticated and detailed model [5][6]. This is perhaps due to lack of guidelines for selecting the most appropriate model and the tendency to believe that the more complex model will likely impress the client. However, such models require a large number of inputs regarding the building design that might not be always available or generally known beforehand. This fact introduces input uncertainties that affect the models' output. In some cases, more complex models are necessary to ensure the usefulness of the model. For detailed information on the behavior of (complex) building energy systems and sub-systems, simpler models might provide inaccurate results even when very accurate inputs are adopted. This inaccuracy is not derived from the input uncertainties, but derived from the modelling abstraction error incorporated in the simplified model. In other cases, increasing the level of model complexity may even decrease the accuracy of the results, due to increasing uncertainties in the input data[7]. How to find the balance between model complexity and the accuracy that is affected by input data uncertainty and abstraction error in the given model, remains one of the biggest challenges.
The combination of the need for decision support for selecting of tools and the balancing act between input uncertainty and abstraction error at different levels of model complexity is the focus of this research.

1.2. **THE CASE OF THE COMPANY**

1.2.1. **Current situation at the company**

With the growing emphasis on sustainability, building system design plays a pivotal role in the design of energy efficient buildings with comfortable indoor environment. This research is in collaboration with a company, which we will refer to as ‘company’. The department Sustainable Mechanical, Electrical and Plumbing (S-MEP) at the company is responsible for building system design decisions related to building energy systems that affect the building energy use and indoor environment.

S-MEP works collaboratively with multiple disciplines, such as architects, civil, mechanical and electrical engineers and the client (i.e. building owners), to design and build energy efficient buildings by providing sustainable solutions that enhance the built and natural environments. Their role as a consultant is to analyze the consequences of building (system) design decisions and to communicate with design team members and clients to make them aware of those consequences. The consequences are mostly expressed in building energy use, thermal comfort, total capital, and operational costs.

S-MEP performs calculations in order to predict energy performance of buildings. The result of those calculations are part of the decision-making process used for multiple reasons, among others: (i) to optimize building energy use, (ii) to compare alternative building (system) designs, (iii) to evaluate these systems and match energy load with energy generation, (iv) to size system components, and (v) to predict thermal comfort. Guaranteed energy savings, or provide compensations or reimbursement in the event of a shortfall in energy savings, is not part of the scope of work of S-MEP. This presents a different risk picture for the company in contrast to Energy Performance Contracting (EPC) projects.

1.2.2. **Research motivation of the company**

At the company, different methods of varying complexities are used to determine building energy performance, ranging from in-house developed spreadsheet tools and simplified calculations to detailed energy simulation software. Commonly, the level of complexity is chosen based on past (individual) experience. This might result in time-consuming detailed energy simulations in cases where simpler methods are more appropriate, and vice versa.

The company wishes to gain more theoretical supported insight into how input parameters influence the output. Furthermore, how different levels of complexity might affect the decisions related to building design is of interest. These insights could help analyzing consequences of choices made in the building design and its systems while using different model complexity levels.

1.3. **RESEARCH OBJECTIVE**

The main objective of this research is the development of a decision support methodology to discover the needed model complexity for building energy performance with regard to formulated design questions. This methodology attempts to quantify the input uncertainties and modelling abstraction errors related
to certain levels of model complexity (the meaning of complexity, input uncertainty and abstraction error are discussed in detail in Chapter 2). Part of this research lays at indicating the trade-off between input uncertainty and abstraction error, which helps to select the fit-for-purpose model complexity.

To select the fit-for-purpose model complexity, the following question has been formulated: what is the minimum required level of model complexity that will produce results within the required tolerances of performance indicators of interest per phase of the project? This question introduces three issues: (i) which modelling approaches representing different complexities levels are currently used at the company to determine the building energy performance, (ii) which (combination of) factors influence the selection of the appropriate complexity level on the predicted building energy performance, and (iii) what is the difference between the output of different complexity levels and how does it influence the decision making process.

1.4. THESIS OUTLINE

Figure 1.1. shows a graphical representation of the way this thesis is structured. The outline of the chapter is as follows:

Chapter 2 starts by giving an introduction in background terminology and introduces the issues of uncertainties and abstraction errors in building performance simulation. Chapter 3 presents the methodology to select the fit-for-purpose model complexity: followed by a method to quantify the abstraction modelling error and input uncertainties. Chapter 4 describes the four selected levels of model complexity, the case study building, uncertainties, and scenarios that are used in this research. Chapter 5 presents an inter-model comparison of the BEStest building case, used to evaluate the building energy simulation tools relative to each other and subsequently describes the causes of discrepancies between the tools. In Chapter 6 the office building case study is carried out in order to illustrate the potential of the fit-for-purpose framework and to offer insight in the effect of model complexity on decision making. Chapter 7 discusses the application of the fit-for-purpose framework. To conclude, Chapter 8 provides the conclusions and recommendations for future research in this domain.
2. TERMINOLOGY AND THE RELATIONSHIP BETWEEN MODEL COMPLEXITY, INPUT UNCERTAINTY, AND ERROR

The choice of the most suitable level of model complexity is often considered as one of the most difficult aspects of the modelling process[6][8]. The choice of the model has impact on all aspects of the project, not only the results but also the consultancy cost of a project, as the choice influences the required time, resources and data to build and run the model. These criteria cannot been neglected, especially in the world of building industry. Currently, the choice of model complexity is mostly based on the users’ expertise [9]. This might result in time-consuming detailed energy simulations in cases where simpler methods are more appropriate. The problem with detailed building energy simulations is the fact that they require a huge amount of input data for model definition. Depending on the phase in the building process, many of these inputs are simply unattainable or may not be yet decided. In other cases, simple models might be used outside of the domain of purpose where the model behaves in a physically correct way. The (strong) simplification of the physical system or/and an incomplete model can result in a loss of accuracy.

Both too complex and too simple models can lead to unreliable analyses, which could result to suboptimal design decisions. In BPS, this could result in larger energy demands, higher operating costs and under- and over-performing building energy systems (i.e. the system is not capable of obtaining and guaranteeing design standards)[6][10]. As it will be very hard, or even impossible, to develop a tool which would satisfy all modelling objectives, there is a need for a fit-for-purpose selection strategy approach. In this research, the models are structured according to their complexity. In this research, the models are structured according to their complexity.

This chapter starts with a definition of model complexity. The meaning of the fit-for-purpose model selection approach is discussed in section 2.2. In section 2.3, we describe the trade-off point between input uncertainty and abstraction error that is used as a starting point for the methodology to select the fit-for-purpose model complexity. In section 2.4, the sort of uncertainties existing in building simulation are discussed. Finally, the challenge of quantifying abstraction errors for deterministic models is described.

2.1. MODEL COMPLEXITY DEFINITION

In this research, the term model complexity is adopted as an important characteristic in simulation modelling. It is defined by Zeigler et al. [11] as a combination of scope of the model, model resolution and the level of interaction between the (input) parameters, components and mathematical expressions used within the model.
Scope of the model refers to how much of the real world is represented [11]. The scope generally depends on where the model boundary is established, generally it can be said that the larger the area of the real world within the model boundary, the greater the number of components in the model. However, depending on the modelling objectives, a real-world portion of interest might be represented in only a few parameters instead of modelling with numerous parameters [3]. Model resolution refers to the number of variables in the model and their precision or granularity [11]. The resolution determines how precisely the scope of the model represents the model. More precisely the component is modelled, the higher the model resolution. We also include a third term for model complexity, the components’ interaction. This level of interaction refers to the inter-components interactions of the mathematical model. It is the way parameters and components are coupled together to from a larger component or mathematical model [11]. The mathematical representations of the basic energy processes form the basis for the building energy consumption prediction.

### 2.2. FIT-FOR-PURPOSE MODEL SELECTION STRATEGY

The building design process is fragmented and consists of frequent revisions and continuous exchange of fragmented information between specialized architectural and engineering personnel. The provided data and information for a building project change over different phases of the design process. BPS models emphasize on different stages as they are built for various purposes. Early design decisions may not require a detailed simulation program to deal with massing or other early design problems [12]. In addition, detailed simulation software requires complementary input information that might be unknown or not yet decided in early design stages. The use of different levels of input detail for building geometry, (sub-)systems and needed ‘input time’ is required at different stages of the design process. Therefore, we encourage to use a suite of tools, which would support a range of model complexity, wherein both simple and complex modelling approaches remain valuable tools.

In order to take correct decisions, and draw the right conclusions arising from the results of a model, it is important to match the complexity of a model with the modelling objectives. Therefore, there is a need for ‘fit-for-purpose’ model selection approach, in which the choice of the model complexity hinges on its purpose. There is broad agreement among model developers that models that are built to fit the purpose are preferable over more complex models [13][14][15]. The meaning of fit-for-purpose can be explained through a model that accomplishes a desired level of explanation or prediction for a given purpose [16] or as a model that is accurate for the purpose at hand [17]. In other means, models should not be more complex than needed for the design or decision purpose [9].

To select a model that is fit-for-purpose, the objective for producing the model should be clearly stated [18]. Therefore, there should be a list of performance indicators that will be used to evaluate design questions being investigated. In this research, the level of model complexity is considered to be fit-for-purpose if it can support design decisions with an acceptable overall level of prediction error for the listed performance indicator(s). This level of prediction error is defined as the sum of the error due to simplification of the physical reality (abstraction error) and the uncertainty associated with parameter estimation (input data uncertainty). In this context, the stage of the building process that corresponds with a certain level of uncertainty is taken into account for selecting the most appropriate model complexity.
2.3. **TRADE-OFF BETWEEN INPUT UNCERTAINTY AND ABSTRACTION ERROR**

There exists a trade-off between input data uncertainty and abstraction error in a prediction model used within a certain design phase of a building. Indicating the balance between these two aspects, could help to select the fit-for-purpose model complexity. This is illustrated in Figure 2.1., where the lowest overall lowest prediction error is considered to be at the intersection of the abstraction error and input uncertainty error. The overall error will not decrease for a more complex model after this intersection point. Therefore, there is no sense adding any additional complexity beyond this point.

The curve that defines input uncertainties might shift, depending on the project’s design phase. Early on a design process, the building design and how the design will evolve are generally unknown resulting in higher design input uncertainty compared to later design phases in which the building design is defined. From Figure 2.1., it can also be concluded that, in cases where the input parameters are highly uncertain, increasing the model complexity will adversely affect the overall error prediction (i.e. the sum) due to the involved uncertainties. This might imply a preference for a lower level of model complexity in early design stages.

![Figure 2.1. Trade-off between model complexity and error in building performance prediction [3][11].](#)

The curve that is decreasing for a higher model complexity illustrates the level of abstraction error. All models will suffer from a certain level of abstraction error as a model is by definition a simplified representation of the reality. Hence, this curve will never reach the y-axis, i.e. no error in building performance prediction.

2.4. **SOURCES OF UNCERTAINTY AND ERROR IN BUILDING ENERGY SIMULATION**

All models, from simple models such as rule-of-thumb models to detailed models based on coupled simulation, suffer from uncertainties and errors. The sorts of uncertainties and errors differ from their nature and controllability among others. In order to investigate what errors and uncertainties affect decision making, we distinguish different sorts of uncertainty and error, see Figure 2.2. We categorize the uncertainties in building energy models by adopting the taxonomy of Rezaee et al. [19].
Depending on the stage of the design process, the exact value of the input parameters might be undecided or unknown. These unknown, uncertain or incomplete parameter values that are used in the simulation model can be categorized to input uncertainties. This kind of uncertainty can be divided in two uncertainties: scenario parameter uncertainty and design parameter uncertainty as is shown in Figure 2.2.

**Figure 2.2.** Sorts of uncertainties in building energy simulation.

The scenario uncertainty is defined as a potential inaccuracy in any phase or activity of the modelling process that is due to lack of knowledge. These kind of uncertainties can generally not be reduced by acquiring more information about the studied system, as the exact value will vary by chance from unit to unit or from time to time. This type can be subdivided into two types: internal and external scenario uncertainties. The internal scenario uncertainty is associated with the scenario of use, such as internal heat sources and occupants behavior. The external scenario uncertainty arises from the boundary conditions, such as weather conditions. In the literature, this uncertainty is also referred to as irreducible uncertainty.

The design parameter uncertainty arises from the low level of information on the design parameters associated with a particular phase of the design process. A subdivision can be made between decided and undecided parameter uncertainty. The decided parameter uncertainty is used to describe the inherent variation associated with parameters for which a design decision has been made and whose values are thus known, at least nominally. For example, consider that the construction of the building envelope has been defined, and hence, its thermal resistance (Re-value) has been decided upon. However, due to improper installation, thermal conductivities or thickness that might be different from quoted values the actual as-built thermal resistance may differ from this decided-upon nominal value. The distribution of the decided parameter uncertainties can be represented by a normal distribution, near a chosen nominal as is illustrated in Figure 2.2. Undecided parameter uncertainty is the second type of design parameter uncertainty and quantifies the lack of knowledge in those aspects of the design that have yet to be settled/decided. By acquiring more information about the building design the undecided design parameter uncertainty can be reduced. This undecided parameter uncertainty will be high early on the design process, in which the undecided parameter uncertainty is represented by an uniform distribution over all the of plausible design decisions, e.g. glass area. At later design stages, these parameters will be defined and, thus, reducing this type of uncertainty. Therefore, the range of uncertainty and the probability distribution of the design parameters will change from a uniform to
normal distribution depending on the phase building’s lifecycle.

The last sources which affect the prediction accuracy in building energy simulation are the errors. Errors can be differentiated between respectively modelling abstraction error and numerical error [3][20]. The first error is due to the modelling abstractions, it occurs by using an incomplete model or/and a simplification of a physical system. As an example, the abstraction of a model can range from representing entire systems with a few parameters, to modelling each heat transfer surface with numerous parameters. The second type of errors are related to converting the mathematical models into a form that can be addressed through computational analysis. This conversion is done in the discretization phase, which deals with questions such as consistency of the discrete equations with the mathematics form of the model, stability of the numerical method, and the chosen time steps.

In this research, it is assumed that the numerical errors are minimized by double-checking of a computer program, expert opinions and decreasing the discretization step for the higher model complexity tools. Therefore, when we refer to ‘errors’, we will be referring only to modelling abstraction errors, unless otherwise stated.

Although the main focus of this research is on the design parameter uncertainties, the effect of internal scenario uncertainty is investigated separately from the design parameter uncertainty. This investigation is done to give information about the influence of each group of uncertainty. The internal scenario uncertainty is assessed, by subtracting and adding a fixed percentage of change in base value for the internal heat sources (lights, equipment, and people). The internal scenario uncertainty is assessed at the final design stage. This uncertainty range is not intended to be realistic, but it is useful for assessing the effect of internal scenario uncertainty on energy performance indicators and thermal comfort.

2.5. **CHALLENGE OF QUANTIFYING INPUT UNCERTAINTIES AND ABSTRACTION ERRORS**

Quantifying the errors due to parameters estimation and abstraction error and its influence on the prediction model is essential to assess the validity of the model [1]. The input uncertainties can be easily quantified, as the input uncertainties corresponds with the model’s output for deterministic model. In contrast, quantifying modelling abstraction errors is more challenging. Information about how to quantify modelling abstraction error is rarely available [20].

For buildings that have yet to be built, measured data is unavailable, making it impossible to obtain information about the abstraction error, by matching the simulation results and the data obtained by measurements. In order to provide some information about modelling abstraction errors in cases where there is no measurement data, a new proposed method for quantifying the abstraction error will be discussed in the section 3.2.
The choice of the best tool for BPS is often viewed as a challenge given the wide range of available tools. As discussed in previous chapter, there is a need for a fit-for-purpose model selection strategy. The selection process requires not only stating the objectives, but should also take into consideration the input uncertainty and abstraction error. This chapter proposed a methodology to select the fit-for-purpose model complexity. Section 3.1, presents a flow chart to identify the fit-for-purpose model complexity, which is based on the abstraction error and input uncertainty. In section 3.2, we propose a new method to quantify the modelling abstraction error, which will be based on the formulated design question and comparative analysis. When this error is quantified for the evaluated model complexity, our method for quantifying the input uncertainty at early and later design stage is described in section 3.3. In section 3.4, the method for the sensitivity analysis is described. In the last section of this chapter a manner for making design choices between selected designs under uncertainty is described.

**3.1. FIT-FOR-PURPOSE FRAMEWORK**

A framework to define and select the fit-for-purpose model complexity is developed, as shown in Figure 3.1. The specification of the model’s purposes is the first step in selecting the fit-for-purpose model complexity. Having stated the objectives, (a set of) performance indicators and requirements of the tools with regard to its objectives should be specified. Depending on the objective(s) and requirements, there will usually be a range of possible tools available that could be represented by various levels of model complexity. The choice of the most appropriate model complexity should be based on the overall lowest prediction error. Therefore, the abstraction modelling error for each level of model complexity as well as the undecided and decided design parameter uncertainty associated with the building phase will be calculated. Subsequently, the associated level of confidence that needs to be placed in the model should be specified.

If the overall level of prediction error is accepted, the model complexity that will have the lowest overall prediction error leads to the most appropriate complexity. In case the calculated level of prediction error is inconclusive, further treatment is necessary in order to reduce the overall prediction error. By incorporating a sensitivity analysis, insight can be given in the contribution of individual parameters to the output or decision variable. Once the most influential parameters are known, treatment can be focused to reduce the undecided parameter uncertainty by making design decisions upon those parameters.
3.2. QUANTIFICATION OF ABSTRACTION ERRORS

A comparative analysis of the selected model complexity levels was performed to obtain information about the abstraction modelling error. For a predefined case-study, in which all input parameters are considered to be certain and known, there will be no input data uncertainty. Hence, the overall prediction error consists of only the abstraction error. It is found in literature, that it is not possible to predict the energy consumption more accurately than ±10-15%, even if all input parameters are known [21]. Therefore, the minimum level of abstraction error is set on 10% for the most complex model that is presumably the most physical correct.

For the abstraction error of the other model complexity levels, the output for different performance indicators for the predefined case study are compared. We quantified the abstraction error of the other model complexity levels by calculating the relative difference between the most complex model and the evaluated complexity level. The abstraction error depends on the selected performance indicator. In
general, the abstraction modelling error (AME) for the evaluated level can be calculated using equation [3.1],

\[
\text{AME}_{\text{PI, EvAluAtEd lEvEl}} = \left( \frac{\text{Output}_{\text{PI, EvAluAtEd lEvEl}} - \text{Output}_{\text{PI, hIghEst lEvEl}}}{\text{Output}_{\text{PI, hIghEst lEvEl}}} \right) \times 100\% + \text{AME}_{\text{PI, hIghEst lEvEl}} \quad [3.1],
\]

where AME_{\text{PI, EvAluAtEd lEvEl}} \% is the abstraction modelling error for the evaluated level for a given performance indicator (PI) expressed in percentages. Output_{\text{PI, EvAluAtEd lEvEl}} is the outcome of the evaluated complexity level for the given performance indicator. AME_{\text{PI, hIghEst lEvEl}} represents the abstraction modelling error of the highest model complexity level. The selected levels of model complexity are discussed in section 4.1. This abstraction error needs to be added to the evaluated complexity level, as each model suffers from a certain minimum level of abstraction error.

### 3.3. QUANTIFICATION OF INPUT UNCERTAINTIES

To study the total uncertainty in the entire input, uncertainty analysis is applied. In this methodology, a Monte-Carlo simulation is used to quantify the input uncertainty. The Monte Carlo method gives the probability distribution of possible results by running the simulation model for a number of scenarios and randomly selecting a different set of undecided and decided parameters. The decided parameter uncertainty is mainly normal distributed and the values are based on literature [22][23][24]. The decided parameters and their distribution are listed in Table 4.3. Unless otherwise noted, the model uses these values except for the undecided parameters that are being explored. For the undecided parameter uncertainty an uniform distribution is assumed. The design parameters related to the volumetric design such as the orientation, floor area, building height, length and width are out of scope of the uncertainty analysis. The reason for this is that the volumetric design is considered to be decided at the conceptual phase, as the building has to suit the needs of the occupants.

In previous research, some guidelines are provided for determining the number of simulations required for the Monte Carlo method. However, these turned out to be too unreliable to apply in general [25][26]. Therefore, the amount of simulations are varied for each model complexity depending on the uncertainty ranges and the amount of parameters. To verify the minimum amount of simulations that give a representative probability distribution, the median and standard deviation of the results are compared.

### 3.4. SENSITIVITY ANALYSIS

A sensitivity analysis has been conducted to identify those parameters that are most influencing a response or decision variable. Two types of sensitivity can be evaluated: (i) individual sensitivities, which describe the influence on predictions of variations in each individual input; (ii) total sensitivities, due to the uncertainties in all the input data [27]. The first type of sensitivity, also referred to local approach [28], individually varies the input parameters and the remaining parameters stay identical at their “base-case” value. The second type, belongs to the global approach, varied all the uncertain parameter simultaneously. Both types of sensitivity analysis are used in this research. In addition,
sensitivity analyses were used to find out more about the prediction error between different complexity levels. The analyses can be used to detect inaccuracies for the ranges of the input parameters or to locate errors in the model. The knowledge gained from this analysis enables more accountable evaluation of the abstraction error. For example, it could highlight design scenarios that maximize best or worst possible outcomes between the complexity levels.

The first step in the sensitivity analysis is to determine the range of the input parameters. For the purpose of assessing the energy performance of a new building using different design options, the input variables should be taken as uniform distributions assuming that these variables are equally probable, as was suggested by Tian [28] and Mechri et al. [29]. The input range used for the sensitivity analysis is expressed in percentage. For example, a fixed range of 25% for most undecided parameters is assumed, except for the temperatures setpoints and the glazing type. The ranges might not represent a realistic uncertainty although they comply with the building code and standards. However, they define a common base for selecting the trade-off between abstraction error and input uncertainty and to compare the sensitivity of different model complexities.

To investigate the relationship between the input and output for the global approach, regression analysis is used as a quantitative measure of sensitivity analysis. The regression method is the most widely used method for sensitivity analysis in building energy analysis [28]. The software SPSS is used to find the standardized regression coefficients (SRC) of the input parameters. The SRC quantifies the changes of the input parameters relative to the output, which means it can be used as relative sensitivity measure (if the input parameters are independent [30]). The coefficients represent the degree of correlation between two parameters, a coefficient close to 1 indicates a strong correlation, a coefficient close to 0 indicates a weak correlation.

With the knowledge of the most influential parameters, i.e. the input parameter with the largest SRC, treatment can be focused to reduce the uncertainty of those parameters or to make the uncertainties accountable.

3.5. MAKING DESIGN CHOICES BETWEEN SELECTED DESIGNS UNDER UNCERTAINTY

For comparison of (architectural) design alternatives, the absolute values obtained from the model are less crucial, as the common belief is that the relative differences between the design is of interest and that the alternatives are based on almost exactly the same assumptions. Therefore, the methodology to select the fit-for-purpose model complexity for comparing different designs and HVAC systems will be slightly different from that of the proposed framework, Figure 3.1.

From a practical point of view, we start with the selection of the most simple level of model complexity which is required for the comparative analysis. For this analysis, the relative differences between the alternatives are of interest. If the result of this analysis provides a clear answer on the question which design or system alternative will result in a better outcome, then an increase of the model complexity is considered not to be necessary. This is illustrated in Figure 3.2a, in which the boxplots do not overlap, meaning that the decision can be made with confidence that the outcome of one alternative dominates on the other one. However, when the boxplots partly overlap the result of the comparison is inconclusive for making a design decision. As there is a change that alternatives might switch places...
in a preference ordering depending on the input parameters this is illustrated in Figure 3.2b. Therefore, an increase in model complexity is required or decisions has to be taken upon the undecided design parameters in order to reduce the uncertainty that the selected option could be outperformed by another option. In case the boxplots are largely overlapping, the design decision has a negligible effect on the investigated PI.

**Figure 3.2a**  Nonoverlapping boxplots illustrate that a design decision can be made, as in all cases Design 2 outperforms Design 1.

**Figure 3.2b** Overlapping boxplots indicate that Design 1 could outperform Design 1, therefore, a design decision can not yet be made.
This chapter starts with a brief description of the selected levels of model complexity from the point of view of the company. With the aim of establishing a common idea of the advantages and disadvantages of the different model complexity levels. In section 4.2, three simulation objectives and their associated performance indicator(s) have been defined. The two building case studies that are under investigation are described in section 4.3. The last section presents three HVAC configurations that are used in this research.

**4.1. CONSIDERED MODELS AND THEIR COMPLEXITY LEVELS**

Given the currently wide range of the available building energy performance tools, we selected four modelling approaches representing the different model complexities that are of interest for the company. Structuring the modelling approaches according to their complexity can help in the search for possible alternative (better) models or tools within the specific level of complexity. Furthermore, this is done in the hope that there will be similarities with previous studies as the level of complexity is the most commonly characteristic used to compare models [4].

*Table 4.1.* shows the four levels of complexity that are used within this project. The levels of complexity can be described as: (i) key figures, (ii) quasi steady-state method, (iii) dynamic building energy simulation using a decoupled approach, and (iv) dynamic building energy simulation using coupled modelling approach. In the remainder of this paper the four model complexity levels are referred to as: Level I, Level II, Level III and Level IV. A higher model complexity is a result of increasing either the level of detail, the scope or the interaction between components.

<table>
<thead>
<tr>
<th>Complexity levels</th>
<th>Description of the level</th>
<th>Selected tool</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level I</td>
<td>Key figures</td>
<td>Based on NEN-norm and experience</td>
</tr>
<tr>
<td>Level II</td>
<td>Quasi steady-state method</td>
<td>Simplified Spreadsheet tool</td>
</tr>
<tr>
<td>Level III</td>
<td>Dynamic building energy simulation using decoupled approach</td>
<td>TRNSYS (building load) + Spreadsheet tool (systems)</td>
</tr>
<tr>
<td>Level IV</td>
<td>Dynamic building energy simulation using coupled approach</td>
<td>TRNSYS (integrated building load and systems)</td>
</tr>
</tbody>
</table>
4.1.1. Description of modelling approach Level I

Level I consists of rule-of-thumb models and key figures derived from practice and experience. This is an important tool for designers and engineers, and it is the traditional method to design HVAC systems [31]. With this level, a quick overview or “concept” of the magnitude of the project at hand can be given. Furthermore, rules of thumb can be extremely useful for approximately calculating a value, quickly verify the work, setting outline targets or rapidly comparing different design options. As handy as the method might be, these rules of thumb must be treated as just approximations, rather than precise models. Therefore, this level is not represented in the BEStest procedure for a qualitative assessment. In this project, the key figures for this level are derived from NEN-EN 12831[32], NEN 5067 [33], and the experience at the company for small to mid-rise office buildings.

4.1.2. Description of modelling approach Level II

Level II refers to a spreadsheet tool that is developed at the company and is rarely used. The purpose of this tool is to evaluate and compare alternative design solutions and systems in early design phases. The building geometry is modelled as a rectangular box and represents one thermal zone. This simplified quasi-steady state model has a physical meaning and is relatively simple to apply, requiring little (computational) time to build and run the model. The quasi-steady state model calculates the energy demand on an hourly basis by subtracting the heat losses (e.g., the energy transferred by ventilation by means of ventilation airflow, the transmission and infiltration through the building envelope) from the heat gains (i.e., energy gain from solar radiation and internal sources).

4.1.3. Description of modelling approach Level III and Level IV

The Dutch building energy software VA114 (Vabi) is commonly used at the company. With the current version of VA114 (version 2.2.1) it is not possible to conduct automatically parametric analyses. Editing the input files containing geometrical and physical parameters in order to conduct parametric studies is unfeasible in the current version of VA114. As a result of this inability, VA114 is considered to be inappropriate for this research. Hence, this tool is used only for inter model comparison for Case A- BEStest, section 5.2.

TRNSYS (version 17.1) has been selected as building energy software to model the building load of Level III and IV, because it contains, among others, the functionality to directly embed other software tools (e.g., Matlab) in a simulation in order to conduct batch processing. In addition, TRNSYS has an extensive library with pre-defined components and flexible approach to model central air systems. A TRNSYS model is described by a set of modules interconnected in a logical manner to solve a particular task. Due to the modular structure of the software, it simplifies to extend existing models to make them fit the user’s specific needs.

The main difference between the last two levels is the components’ interaction between the building load and its systems. In Level III, the building load is first calculated in TRNSYS; then, this result is used as an input to evaluate the performance of HVAC systems in the form of another Excel spreadsheet tool. The third level follows a decoupled approach, which can be referred to as sequentially coupled
Complexity levels, simulation objectives, and case study

approach. As the name reveals, the models run in sequence, i.e., the building load is first calculated; then, this result is used as an input to evaluate the performance of HVAC systems in a spreadsheet based tool.

Level IV follows a coupled approach, also referred to as fully integrated [3], by taking into account the interaction between load, system and plant model, and allowing the system deficiencies to be taken into account when calculating the building thermal conditions. The models iterate within one time step. This approach is not commonly used within the company. However, this modelling approach is selected to provide insight if a higher model complexity might be required for some purposes.

Another important difference is the modelling approach for the HVAC control. Level III used the concept of “ideal” control, meaning that the heating and cooling energy demand will be adjusted to satisfy the set point requirements which are determined from the known load. The heat flux can be directly actuate within this level of model complexity where in reality this can only be done indirectly, by changing a valve/damper position[34]. The explicit control function is not specified in this level. In contrast, the control strategies are modelled in the Level IV. The controllers for the HVAC are represented by equations that must be satisfied in every simulation step. The controllers direct the interaction between building and system as well as interactions between components within the system.

4.2. SIMULATION OBJECTIVES AND PERFORMANCE INDICATORS

The developed fit-for-purpose framework that is introduced in Section 3.1 is applied into practice for an office building, that will function as an example of a design process.

The first step in selecting the fit-for-purpose model complexity is defining the modelling objectives as mentioned before. From company perspective, three design objectives were defined that are of interest and used to investigate how model complexity affects the design decisions regarding the objectives. The following objectives were used as an input to demonstrate the developed fit-for-purpose framework: i) optimizing energy efficiency with the building design, ii) selecting HVAC systems, and iii) sizing the equipment capacity composing those systems.

Having stated the objectives, a set of performance indicators (PIs) of interest were specified. Figure 4.1. shows the key PIs for the three formulated objectives. Moreover, this figure illustrates the relation between the defined design objectives and the building phase and the changing level of information on the project. The building phase was considered analogously to the level of information on the design parameters.

In early design phase, the role of the company is to analyze consequences of building design decisions and to advise architects and clients on how to reduce building energy demand with the building design. Making conscious design decisions at early design stages when there are undecided parameters requires accounting for the fact that we do not know what those other undecided parameters will be after future decisions. Dealing with the uncertainty of undecided parameters impose a challenge on making performance-based decision.
To support advice on early design decisions this type of uncertainty needs to be considered, helping to prevent situations in which a later decision counteract the energy performance of an earlier design decision. For comparing alternative building designs solutions, the relative heating and cooling energy demand are of interest rather than an exact amount of energy demand. Therefore, the relative energy demand is considered to be the key PI for optimizing the building design.

Once there is an accurate understanding of optimizing the building design, the next iterative step in the design process involves the selection of equipment and the design of the HVAC system to meet the predicted heating and cooling loads of the building. The ratio between heating and cooling can be helpful when selecting the equipment to meet the building load. This relationship might be used for selecting additional building energy system. For example, by designing an aquifer thermal energy storage (ATES), one might decide to utilize this aquifer in conjunction with or without heat pumps, cooling towers and dry coolers depending on this relationship. Therefore, this ratio can be an important consideration together with the total annual building energy consumption for selecting the HVAC system.

For sizing the equipment the annual building energy consumption in kWh/m² per annum is used an indicator of the building energy performance. This indicator is often the most significant factor of interest to building energy analysts [35] and can be calculated by dividing the building energy consumption by the total gross floor area of the building. Another important set of PIs that need to be considered for sizing HVAC systems are the peak heating and cooling loads.

The internal scenario uncertainty is assessed on the basis of overheating risk at later design phase for different HVAC configurations. This is accomplished by counting the number of hours that indoor air temperature exceeds 24.5°C and 25.5°C. For the case-study, allowing discomfort during maximum 5% of working hours is seen as realistic and economic target value in the trade-off between energy and comfort. As a result, this amounts to an allowed number of 100 overheating hours.
4.3. BUILDING CASE STUDY DESCRIPTION

The BES test qualification case 600 and case 900 were initially put into practice to perform qualitative assessment and to demonstrate the methodology to define the fit-for-purpose model complexity level. A brief description of the BES test case is found in subsection 4.3.1. Due to the simple nature of this building and the fact that the BES test does not always comply with the Dutch building code, a more representative case study was set-up and used as a second case study in subsection 4.3.2.

4.3.1. Case A – BES test case

Two BES test qualification cases, a lightweight (case 600) and heavyweight (case 900) building, were used for the inter-model comparison. The BES test building is a rectangular, single zone (8 m wide × 6 m long × 2.7 m high) with no interior partitions and 12 m² of windows on the southern exposure. For further details refer to Section 5.2.1 of ASHRAE Standard 140-2007 [36]. The case 900 used the same building model as the case 600 except that the wall and floor construction are changed to heavier materials. For both cases, two climates were applied namely the originally Denver climate file and the climate file of the Netherlands based on NEN 5060:2008.

4.3.2. Case B- Dutch office building

With the emphasis on energy efficient buildings, the base office building under investigation complies with energy efficiency codes and standards, low infiltration rates, and lower artificial lighting and plug loads. The base case model forms a very important part in the analysis because all subsequent calculations and analyses are based on the comparison with it. The base case model is a rectangular, eight-zone Dutch office building. The plan and impression of the case study are shown in Figure 4.2.

Office buildings belong to the building types with clearly defined occupancy pattern [40]. The building is considered to be occupied during weekdays between 7am and 7pm only, and the indoor thermal condition and air quality has to be strictly controlled in that period. Zone air temperatures are controlled by dual setpoint thermostats, which keep zone temperature above 20°C during heating period and below 25.5°C during cooling period. During unoccupied hours there is a night setback of

Figure 4.2. Plan section of Case Study B (left) and impression of office building (right).
17°C. Fresh air was introduced to meet minimum requirements according to NEN-EN 15251 [38] and NEN 1087 [39] in order to obtain indoor climate class A.

*Table 4.2.* gives the data and information for the base case building at early design stage. The office has typical construction materials that comply with the benchmark. Values for the material properties are defined in *Table 4.3.* Apart from the building descriptions, another important factor in building simulation is the external weather data. The Dutch weather data based on NEN 5060:2008 (ontw.) was used.

*Table 4.2.* Level of information known at early design stage for the design of a Dutch office building.

<table>
<thead>
<tr>
<th>Information known at early design stage</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Location: The Bilt, the Netherlands</td>
<td></td>
</tr>
<tr>
<td>Building type and storeys: Office building, one storey and 8 zones</td>
<td></td>
</tr>
<tr>
<td>Floor and roof area: Total gross floor area = 267 m²</td>
<td></td>
</tr>
<tr>
<td>Dimensions and heights: 19 m · 14 m; floor-to-floor = 3.5 m</td>
<td></td>
</tr>
<tr>
<td>Climate: Indoor climate class A; Ventilation 60 m³/h p.p; Temperature between 20-25.5°C during occupation hours, at night : minimum temperature 17 °C</td>
<td></td>
</tr>
<tr>
<td>Occupation hours: Mon.-Fri. 08:00 - 18:00, Sat. and Sun. closed</td>
<td></td>
</tr>
</tbody>
</table>

*Table 4.3.* Thermophysical properties and uncertainties for the decided parameters *(Macdonald [22], Hopfe [23], and Hoex [24]).*

<table>
<thead>
<tr>
<th>Decided parameters</th>
<th>Unit</th>
<th>Distr.</th>
<th>[µ]</th>
<th>[σ]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Density</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Concrete slab</td>
<td>[kg/m³]</td>
<td>[N]</td>
<td>2179</td>
<td>149</td>
</tr>
<tr>
<td>Concrete block (wall)</td>
<td>[kg/m³]</td>
<td>[N]</td>
<td>1900</td>
<td>29</td>
</tr>
<tr>
<td>Concrete reinforced (roof)</td>
<td>[kg/m³]</td>
<td>[N]</td>
<td>2310</td>
<td>225</td>
</tr>
<tr>
<td>Fiberglass insulation</td>
<td>[kg/m³]</td>
<td>[N]</td>
<td>12</td>
<td>1</td>
</tr>
<tr>
<td>Dense EPS slab insulation</td>
<td>[kg/m³]</td>
<td>[N]</td>
<td>15</td>
<td>1</td>
</tr>
<tr>
<td>Roof materials</td>
<td>[kg/m³]</td>
<td>[N]</td>
<td>1800</td>
<td>229</td>
</tr>
<tr>
<td>Specific Heat</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Concrete</td>
<td>[J/kgK]</td>
<td>[N]</td>
<td>1.0</td>
<td>0.1</td>
</tr>
<tr>
<td>Fiberglass insulation</td>
<td>[J/kgK]</td>
<td>[N]</td>
<td>0.8</td>
<td>0.1</td>
</tr>
<tr>
<td>Dense EPS slab insulation</td>
<td>[J/kgK]</td>
<td>[N]</td>
<td>0.2</td>
<td>0.1</td>
</tr>
<tr>
<td>Absorption coefficient - concrete</td>
<td>[-]</td>
<td>[N]</td>
<td>0.7</td>
<td>0.0</td>
</tr>
<tr>
<td>Absorption coefficient - insulation</td>
<td>[-]</td>
<td>[N]</td>
<td>0.4</td>
<td>0.0</td>
</tr>
<tr>
<td>Emissivity coefficient - concrete</td>
<td>[-]</td>
<td>[N]</td>
<td>0.9</td>
<td>0.0</td>
</tr>
<tr>
<td>Emissivity coefficient - insulation</td>
<td>[-]</td>
<td>[N]</td>
<td>0.9</td>
<td>0.0</td>
</tr>
</tbody>
</table>
4.4. BUILDING SYSTEM CASE STUDY DESCRIPTION

To meet the indoor requirements, an HVAC system needs to be designed and installed in order to deliver the required building energy demand. An HVAC system is usually divided into two parts: primary HVAC system and secondary HVAC system. The primary HVAC system is composed of equipment which generates heating/cooling energy such as boilers and chillers. This energy is distributed through a building by a secondary HVAC system in order to respond to a building cooling/heating demand.

To assess the overall building energy performance it is necessary to analyze the correlation between building energy demand and the performance of the HVAC systems. In most circumstances, the amount of energy required by the HVAC system does not equate building demand [40]. The HVAC system may show different energy performance, as a result of the HVAC system's characteristics and operational conditions that are affected by the thermal load and behavior of the building. In this research, the primary system is beyond the scope of this research in which we address secondary HVAC system only.

The second modelling objective as formulated in section 4.2 is the selection of the HVAC system. For that purpose, three HVAC configuration systems have been coupled with the office building and simulated in the different model complexity levels. All the HVAC configurations consist of a radiator and an all air conditioning system with Constant Air Volume (CAV). The CAV keeps as the name revealed the air volume flow rate constant while varies its supply air temperature according to the cooling demand of the warmest zone. The main difference between the configurations is the type of heat recovery method. The control strategy for the heat recovery is unaffected in the configurations. The heat recovery is bypassed if:

\[
\begin{align*}
&T_{\text{room}} > T_{\text{setpoint, heating}}; \\
&T_{\text{ambient}} > T_{\text{room}}; \\
&T_{\text{ambient}} > 12^\circ\text{C}.
\end{align*}
\]

If \(T_{\text{room}} > T_{\text{setpoint, heating}}\) or/and \(T_{\text{ambient}} > T_{\text{room}}\) the cold recovery is bypassed.

**HVAC configuration 1: twin-coil heat recovery**

In HVAC configuration 1 the outdoor air is pre-treated by a twin-coil heat recovery unit (HRU) which exchanges heat between supply air stream and exhaust air. The supply- and exhaust flows are strictly separated; therefore no moisture recovery from the supply air occurs. The effective efficiency of twin coil heat recovery units ranging from 40-60%. An efficiency of 45% is used for the first HVAC configuration in this research.

**HVAC configuration 2: cross flow heat exchanger**

A cross flow heat exchanger is installed in the second HVAC configuration. As the name itself suggests the design of the cross flow plate heat exchanger forces the exhaust airflow and the supply airflow to crosses between them. In contrast to twin-coil heat recovery, the cross flow heat exchanger have a higher thermal efficiency. In this research an efficiency of 75% is used. Besides heat recovery from hot ventilation air during winter, cold recovery in a cooled building is possible in the same way from the relative cold inside air during summer.
HVAC configuration 3: cross flow heat exchanger in combination with indirect adiabatic cooling
The last configuration added Indirect Adiabatic Cooling (IAC) to HVAC configuration 2, as is illustrated in Figure 4.3. To provide adiabatic cooling, water is sprayed into the (warm) exhaust air stream before entering the heat exchanger. Through the process of evaporation sensible heat is removed from the air and effectively lowers its temperature. The adiabatic efficiency is “the ratio between the actual cooling of the supply air temperature and the theoretical maximum achievable cooling in the process, the cooling limit temperature”. In literature it is found that the typical efficiency of indirect evaporative coolers is 75% [41][42].

Figure 4.3. HVAC configuration 3, mechanical ventilation with indirect adiabatic cooling and radiator.
5. QUALITATIVE ASSESSMENT AND MODEL COMPARISONS

The use of BPS tools should offer a great potential for energy savings and aid the process of decision making. The users of such tools must have confidence in the tools and should have knowledge about their accuracy. Therefore, validation and testing is a necessary part of any software development process [43]. Given the assumptions made regarding input information and the dynamic occupant usage of buildings, the prediction of absolute energy values of an energy simulation is rarely accurate [44]. To obtain absolute predicted values that match more closely the actual values of the building energy consumption, models need to be calibrated with actual measurements. As a result of the lack of measurement data in this research and the challenge for modelling the dynamic human behavior, the calibration was outside the scope of this research.

In this chapter, the well-known validation procedure the BEStest (Building Energy Simulation Test) was used to get a feeling for the selected tools and to assess the position of the tool in comparison with each other. The BEStest procedure, which was developed by the International Energy Agency (IEA) in 1995, was used to test and diagnose the building energy simulation tools relative to each other and state-of-the-art tools [45]. The BEStest defined acceptable boundaries for evaluated performance indicators, making it possible to check whether the tools produce results which fall within these boundaries.

In section 5.2, the results are given for the two BEStest building cases, a lightweight and heavyweight case. For the lightweight building case, a couple of parameters are varied in order to observe if the model responds logically. In section 5.3, some interesting observations that are found in literature about the results supplied by simplified quasi-steady state models and TRNSYS are described. Then, we give some possible explanations for the discrepancies between the Level II and TRNSYS by identifying some key issues of Level II. In the end, we provide some concluding remarks and some adjustments to improve the accuracy of Level II.

5.1. HARMONIZATION OF INPUTS

Despite our efforts to provide identical input parameters for the qualitative assessment, differences exist due to different modeling requirements between the selected tools. This section will outline some of the more important differences that exists between Level II and TRNSYS.
**Climatic Data.** Originally, the Level II tool used the Test Reference Years (TRY) weather file. This file represents weather data of a single year that has been compared to the original multi-year series of the data. As no single year can represent the typical long-term weather patterns, Hensen [43], recommends users of energy simulation programs to avoid using single year, TRY-type weather data. Therefore, meteorological multi-year weather data are used for model comparison and kept identical for both levels.

Level II required the incident solar radiation on vertical surfaces as an input. However, in most weather files the horizontal solar radiation is given. Therefore, the solar radiation on horizontal surfaces had to be converted in vertical surfaces, this is done by the solar radiation processor of TRNSYS. This processor calculates the solar radiation on tilted surfaces for (user-defined) weather files and sun position according to well accepted algorithms [44].

**Geometry.** The building geometry in Level II is modelled as a rectangular box and represents one thermal zone. Consequently, there are no different thermal zones. The spreadsheet tool does not allow situations for simultaneous heating and cooling, as the energy demand is the result of the heat gains minus the heat losses.

**Material properties.** The thermal resistance is the only material property which is used for the building envelope. The material properties of individual layers and composite walls are neglected in Level II. Among others, thermal capacitance, density, emissivity, and absorptivity. The shading coefficients, number of panes, and absorptivity of the windows are not considered in the spreadsheet. The frame of the window and shading devices are not considered as well. In case non-applicable input values for Level II were found, these inputs were simple disregarded.

### 5.2. RESULTS

#### 5.2.1. BEStest model comparison

Level II does not meet the BEStest criteria for annual thermal cooling and heating demand, as is shown in Figure 5.1. The predicted values for both annual heating and cooling lay well above the upper limit. The dynamic simulation tools, VA114 and TRNSYS, complied with the BEStest limits and their results are comparable. The difference between these two is less than 5% for the total annual thermal cooling and heating demand. Figure 5.2 shows the peak heating and cooling loads. Only the peak heating load calculated by Level II remained within the BEStest boundaries for the lightweight case, case 600. For the lightweight case the percentage difference was equal to 28% for annual thermal heating and 64% for annual thermal cooling.

![Figure 5.1. Results model comparison heating energy demand (left) and cooling energy demand (right) for the BEStest case 600, the dotted line represents the boundaries.](image)
Figure 5.2. Results model comparison peak heating load (left) and peak cooling load (right) for the BEStest case 600, the dotted line represents the boundaries.

Table 5.1 presents the results of a comparison between the tools for both the light-weight building case and the heavy weight building, case 900. Changing the thermal capacity of the building envelope, reduced the heating energy demand by 32% for VABI and 34% for TRNSYS. Likewise, for the cooling energy demand a reduction of 34% for VABI and 35% for TRNSYS was observed. On the contrary, the heating and cooling energy demand calculated by Level II showed to be insensitive to the change of thermal capacity. Therefore, the prediction inaccuracy significantly increased for a high mass building (case 900), up to 280% for annual heating. For buildings with a high thermal capacity the Level II tool should not be used for predicting absolute values for the energy demands and peak loads.

The results of TRNSYS and VA114 showed a good agreement. For the peak load calculations, the percentage differences between VA114 and TRNSYS grow up to 10%. Neymark et al. [36] found that VA114’s diffuse radiation is about 8% higher than the other programs, among other TRNSYS, this might explain the higher cooling peak load deviation between the dynamic tools.

Moreover, the ratio between heating and cooling energy demand derived from Level II was not comparable with dynamic simulation tools. Since average ratio differences of more than -20% for the BEStest cases were found. This ratio is important for load and demand management (e.g. for assessing the potential of using thermal energy storage).

A comparison of the heat losses (infiltration and transmission losses) for the BEStest case 600, is shown in Figure 5.3. Similar trends and recognizable trends with reality can be observed for the calculation of the heat losses. A large discrepancy between the hourly solar heat gains entering the building calculated by TRNSYS and Level II was found, as illustrated in Figure 5.4. To determine if the difference in solar heat gains entering the building causes the overestimation in cooling energy demand prediction, the solar heat gains of Level II are replaced by the vertical solar radiation that are derived from TRNSYS.
It should be noted that without the use of TRNSYS this input cannot be generated. The adjusted version showed a similar trend with TRNSYS, although a slightly higher offset can be observed as can be seen in Figure 5.4. This offset resulted still in an overestimation of the summed monthly heat gains entering the building, however, a better agreement compared to the original Level II was found for the solar heat gains.

To investigate if the equation used in Level II for calculating the energy demand causes the discrepancy in energy prediction, the equation that is used to calculate the heating and cooling energy demand for Level II is also applied for the TRNSYS model. This equation, that is stated in section 4.1.2., is the sum of the hourly heat gain energy (internal heat gains and solar gains) minus the heat loss energy (transmission losses, infiltration losses and ventilation losses). Figure 5.5 compares the output of the TRNSYS model for this sum with the monthly energy demand calculated by Level II and TRNSYS. In the figures, this sum of the heat gain and loss energy is called TRNSYS-heat balance. The monthly heat balance calculated by TRNSYS showed to be more comparable with the heating energy demand calculated by Level II. However, the monthly heating energy demand derived from TRNSYS significantly decreased compared with the sum of the monthly heat balance. A higher difference between the cooling energy demand of Level II and the sum of the monthly heat balance of TRNSYS was found.
Figure 5.5. Comparison between the monthly energy demand derived from Level II, TRNSYS and the sum of the hourly heat gain energy minus the heat loss energy calculated for TRNSYS (the heat balance) for the case 600. The left half of the figure represent the monthly heating energy demand and the other half the cooling energy demand.

5.2.2. Sensitivity analysis

The sensitivity analysis was used to find out more about the prediction error between different complexity levels. The analysis can be used to detect inaccuracies for the ranges of the input parameters or to locate errors in the model.

For the BEStest building case the local sensitivity analysis was used to detect inaccuracies for the ranges of the input parameters or to locate errors in the model. This analysis belongs to the class of the one-factor-at-a-time method [28]. The input values are listed in Table 5.2., the adopted range of input parameters is based on Struck et al. [46]. The result of the sensitivity analysis can be seen in part of the result of the sensitivity analysis can be seen in Figure 5.6 and Figure 5.7. The input parameter with relative the largest variation has the most influence on the output. For both levels the same input parameter was indicated as most influential for heating and cooling energy demand. The glass type has the most influence on the heating energy demand. For the cooling energy demand the window to wall ratio (WWR) has the most influence. The cooling energy demand showed to be more sensitive to the change of WWR for Level II than for TRNSYS.

<table>
<thead>
<tr>
<th>Bestest parameters</th>
<th>Unit</th>
<th>Distr.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Re value wall</td>
<td>[m² K/W]</td>
<td>[U]</td>
<td>2.5</td>
<td>4.0</td>
</tr>
<tr>
<td>Re value roof</td>
<td>[m² K/W]</td>
<td>[U]</td>
<td>2.5</td>
<td>4.0</td>
</tr>
<tr>
<td>WWR South</td>
<td>[-]</td>
<td>[U]</td>
<td>0.5</td>
<td>1.0</td>
</tr>
<tr>
<td>Glass U-value</td>
<td>[W/m²K]</td>
<td>[fixed]</td>
<td>1.1</td>
<td>2.8</td>
</tr>
<tr>
<td>performance G-value</td>
<td>[-]</td>
<td>types</td>
<td>0.8</td>
<td>0.7</td>
</tr>
</tbody>
</table>
From these figures, the interactions between the input parameters and the output cannot be considered. Therefore, a scatterplot depicted in Figure 5.8. shows the interaction of the window surface on the heating and cooling energy demand. The figure shows that there is a linear correlation for the heating and cooling energy demand for both Level II and TRNSYS. The scatterplot also shows the larger variation in cooling energy demand for changing the window surface of the BEStest building case study.
5.3. DISCUSSION

By comparing the absolute values derived from the simplified spreadsheet tool and the dynamic simulations tools a disagreement was found, especially for the cooling energy demand prediction. The cause of this disagreement was not clear. Furthermore, the question remains what can be reasonably expected from the results of simplified building models compared to the results supplied by a detailed simulation software. Therefore, section 5.3.1. started with a literature review of comparative studies of energy performance between (quasi-steady state) simplified building models and TRNSYS. Then, some possible explanations for the discrepancies between the Level II and TRNSYS by identifying some key issues of Level II are given in section 5.3.2.

5.3.1. Previous comparative studies

A number of studies have been carried out in the past that compared TRNSYS with (quasi-steady state) simplified building models for predicting thermal energy demand. Beccali et al. [45] performed a comparative analysis of TRNSYS and two simplified models for calculating the cooling energy demand on a limited building typology. Both simplified models (one model is defined by the Dutch NEN 2916[46] and the other is developed by Schibuola[51]), showed quite a large deviation relative to the forecasts of the dynamic TRNSYS model; on average equal to 50% in the Dutch case and 40% in the Schibuola case. This study also observed, that in most cases the prediction errors increased as the dimensions of the building increased.

In 2010, Vartires et al. [49] compared the building cooling energy demand calculated by TRNSYS to two simplified building models. For the model using a monthly calculation approach, the cooling energy demand was 93% higher in comparison with TRNSYS. The second simplified building model performs hourly calculations, using the CODYBA software[50]. Even though the model complexity was increased, the quality of the results did not increase. A difference of about 90% for the cooling energy demand was revealed compared to TRNSYS.

A recent comparative study between stationary and dynamic models of Evangelisti et al. [51] stated that simplified stationary models are poorly representative of a real building performance, especially for the cooling energy demand. Three building types were considered, an old building, a house, and a flat. Regardless of the type, the simplified models overestimated about 25%–30% the energy demand for heating. In contrast, the simplified building types gave completely unreliable results to predict the energy demand for cooling. For the flat, a very large percentage difference equal to 114% was observed for the cooling energy demand.

Summing up, previous studies have found that most simplified (quasi-steady state) building models are poorly representative for predicting the cooling energy demand with respect to TRNSYS. With one exception (the Schibuola model), the cooling energy demand values obtained by simplified models overestimated the energy demand for cooling compared with the values calculated under dynamic conditions, using TRNSYS software.

5.3.2. Sources of discrepancies for Level II

Level II required incident solar radiation on the vertical window surfaces. However, the level does not contain an algorithm for converting the horizontal solar radiation into vertical solar radiation on each orientation. In order to improve the accuracy of the solar heat gains prediction for Level II, the
algorithm of TRNSYS was used to convert the horizontal solar radiation into vertical solar radiation on each orientation. With the help of TRNSYS’ algorithm, a better agreement for the prediction of solar gains through windows was found, as can be seen in Figure 5.4. The solar gains entering the building are slightly higher in the spreadsheet tool compared to TRNSYS. This offset might be caused by the fact that the long-wave absorption, the convective and conductive heat transfer of the window frame are not taken into account. The omission of these effects could cause higher solar gains entering the building, and thus increases the net cooling energy demand. Even though a more accurate prediction of the solar gains is provided as an input for Level II, still significant differences remained between Level II and dynamic simulation. The results show comparable annual trends and values for the transmission losses and infiltration losses. Therefore, the discrepancy is not caused by the calculation of the solar gains as well as the prediction of the energy losses. The discrepancy in prediction apparently was due to neglecting key processes, such as the thermal capacity, that influence building energy demand, resulting in a large disagreement for the prediction of absolute values in comparison with TRNSYS. This is illustrated in Figure 5.5 that showed a significant difference between the outcome of TRNSYS and the outcome of the TRNSYS model by applying equation which is used for calculating the energy demand of Level II.

An important material property that is omitted entirely in Level II is the thermal capacity, that is not taken into account in the spreadsheet tool. As a result, the heating and cooling energy demand calculated by Level II showed to be insensitive to the change of thermal capacity. On the contrary, in TRNSYS the effect of changing thermal capacity significantly decreased the heating and cooling energy demand by respectively 34% and 35% for the BEStest case. This reduction is caused by the fact that TRNSYS takes into account the structure’s thermal inertia and in particular the fact that during the night, the building releases the heat stored during the day. In Level II the thermal energy storage behaviour is not considered nor does it take into account an utilization factor. Thus, the prediction accuracy of Level II decreased for high thermal mass buildings, case 900.

Other simplified tools, such as CASAnova and the model defined by the Dutch NEN 2916 [46], use an utilization factor in order to take account take into account the usage of the free contributions due to the thermal capacity. The aim of this factor is to consider the effect of the building envelope thermal inertia and of the mismatch between thermal losses and thermal gains Level II lacks such a factor to take into account the effects of energy stored in materials and the mismatch. The usage of free contributions due to the thermal capacity is important for accurate energy prediction.

Another cause for the discrepancies in outcome is the calculation method for the indoor room temperature. Figure 5.9 shows a comparison of the indoor room temperature calculated by Level II and TRNSYS. A diurnal variation of temperature during the year is not implemented in Level II. Thus, in summer months the indoor temperature at night is cooled to night setback temperature (17 °C) while TRNSYS allows a diurnal variation between minimum temperature and maximum temperature. In addition, the calculation of the room temperature derived from Level II is only based on the thermostat set points and ambient temperature. Hence, the indoor temperature is not affected by internal and external heat gains, nor does it consider interzonal heat gains/losses. Assuming a setpoint for the operative temperature is not realistic in most of the cases [51]. In order to obtain the setpoints, higher fluctuations of indoor room temperature are observed for Level II. The deviation in room temperature leads to small discrepancies in the calculation of the heat losses (transmission and infiltration losses) which are, among others, depended on the indoor air temperature. Consequently, this discrepancy attributes to higher calculated heating and cooling energy demand of Level II.
Figure 5.9. Comparison between the indoor air temperature setpoints of Level II and indoor air temperature calculated by TRNSYS. The setpoints are used to calculate the transmission and infiltration losses in Level II.

TRNSYS used heat balance models that characterize the thermal behavior of the room air by solving energy balance equations for the zone air and for the interior and exterior surfaces for estimating the building energy demand. These equations are combined with those for transient conduction heat transfer and weather conditions' data. The mathematical description of the air heat balance and surface heat balance goes beyond the scope of this research. However, the predominant source of disagreement in the prediction of Level II appeared to be in the calculation of the building energy demand. Therefore, the terms that are unable to model in Level II and might cause this disagreement are summarized:

- the surface and infrared radiation exchange between walls and/or windows;
- the wall gains or losses due to the heat flow to the wall or window surface;
- the coupling gains or losses due to (inter-zonal) air flow from zone or boundary condition;
- dynamic indoor air temperature and flow distribution;
- ground heat transfer;
- the energy stored in materials and zone, calculated with capacitance of air and additional materials.

5.4. CONCLUSION

Even though only a small part of the BEStest procedure was carried out, the results of Level II showed that the spreadsheet tool was not able to realistically reproduce the energy performance of the building. The absolute values derived from Level II showed significant discrepancies compared to TRNSYS. The prediction inaccuracy increased significant for the heavyweight case. The primary conclusion of this research is that the predominant source of disagreement is the equation used to predict the building energy demand. The equation omits key processes that influence building energy demand resulting in a model with poor predictive ability for absolute values. The use of the results of Level II is not advisable for accurate building energy performance prediction.

In line with previous comparative studies of simplified (quasi-steady state) building models and TRNSYS, the spreadsheet tool showed higher values for the heating and cooling energy demand caused by omitting dynamic effects compared to dynamic simulation software, TRNSYS. The reported results
highlight the weakness of simplified tools for the prediction of cooling energy demand. In order to improve the overall accuracy of building energy prediction of Level II compared to dynamic simulation, two improvements have been made. First, the control strategy is improved. Second, the hourly solar gains entering the building that are derived from TRNSYS are used as an input for Level II in the remainder of this research.

In the light of these drawbacks, one might argue that the applicability of simplified tools is very limited. However, this might not be the case considering the huge data effort requested for calculations with dynamic tools and the data which might not be always available or yet defined. Depending on the purpose, simplified building models could remain valuable, as the validation technique might differ. For comparison of architectural design alternatives, the absolute values obtained from the model are less crucial. As different design alternatives are based on almost exactly the same assumptions and the common belief is that relative differences in the simulation results are reliable. However, if building usage patterns are dependent on the type of design alternative, the comparison of design alternatives may provide less accurate comparison results.
For the case study building the proposed fit-for-purpose framework, as illustrated in Figure 3.1. is applied into practice. In this chapter the results of it are presented, starting with section 6.1, in which the abstraction modelling error of Level II is defined. Next, conducting an uncertainty analysis on undecided and decided design parameters is needed for selecting the fit-for-purpose model. Results of this uncertainty analysis on different energy performance indicators are provided in section 6.2. To identify the parameters that contribute most to the uncertainty section 6.3 presents the results of a sensitivity study that is conducted. Furthermore, this chapter complements the fit-for-purpose model complexity by investigating the influence of model complexity on decision making. In section 6.4., the results of a comparative study between two competing alternative designs and three HVAC configurations are reported.

6.1. ABSTRACTION ERROR

The relative difference between Level II and TRNSYS is used to calculate the abstraction modelling errors (AME) of Level II. Table 6.1. presents the relative difference and the AME of Level II for the office reference building. The stated AME includes the minimum abstraction modelling error of Level IV. As mentioned before, this minimum level is set on 10% for each energy performance indicator. Despite the modification of Level II enumerated in section 5.4., both annual thermal heating and cooling demand are higher compared with results derived from TRNSYS. This overestimation was previously observed for the BEStest cases. The highest percentage difference between Level II and TRNSYS, 49%, is found for the annual thermal cooling demand.

<table>
<thead>
<tr>
<th>Office building case</th>
<th>Relative difference</th>
<th>AME</th>
</tr>
</thead>
<tbody>
<tr>
<td>Annual Heating Energy demand [%]</td>
<td>36%</td>
<td>46%</td>
</tr>
<tr>
<td>Annual Cooling Energy demand [%]</td>
<td>49%</td>
<td>59%</td>
</tr>
<tr>
<td>Peak Heating Load [%]</td>
<td>27%</td>
<td>37%</td>
</tr>
<tr>
<td>Peak Cooling Load [%]</td>
<td>44%</td>
<td>54%</td>
</tr>
<tr>
<td>Annual Energy demand [%]</td>
<td>43%</td>
<td>53%</td>
</tr>
</tbody>
</table>

Table 6.1. Relative difference between Level II and TRNSYS and defined abstraction modelling error of Level II.
6.2. **UNCERTAINTY ANALYSIS**

The level of information associated with a particular phase of the building design process affects the design uncertainty parameter. This uncertainty (i.e. decided and undecided design parameters) is quantified by the Monte Carlo simulation. The decided design parameters, which describe the inherent variation associated with parameters for which a design decision has been made, and their normal distributions are depicted in *Table 4.3*. The undecided parameters and their range are listed in *Table 6.2*.

*Table 6.2. Undecided design parameters and their range.*

<table>
<thead>
<tr>
<th>Undecided parameters</th>
<th>Unit</th>
<th>Distr.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Revalue wall</td>
<td>[m² K/W]</td>
<td>[U]</td>
<td>5.5</td>
<td>7</td>
</tr>
<tr>
<td>Revalue roof</td>
<td>[m² K/W]</td>
<td>[U]</td>
<td>6</td>
<td>7.5</td>
</tr>
<tr>
<td>North</td>
<td>[m²]</td>
<td>[U]</td>
<td>26</td>
<td>33</td>
</tr>
<tr>
<td>South</td>
<td>[m²]</td>
<td>[U]</td>
<td>30</td>
<td>36</td>
</tr>
<tr>
<td>East</td>
<td>[m²]</td>
<td>[U]</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>West</td>
<td>[m²]</td>
<td>[U]</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>Infiltration</td>
<td>[ACH]</td>
<td>[U]</td>
<td>0.1</td>
<td>0.2</td>
</tr>
<tr>
<td>Uvalue glass</td>
<td>[W/m²K]</td>
<td>[U]</td>
<td>1.1</td>
<td>1.4</td>
</tr>
<tr>
<td>Gvalue glass</td>
<td>[-]</td>
<td>[U]</td>
<td>0.5</td>
<td>0.6</td>
</tr>
<tr>
<td>Shading coefficient</td>
<td>[-]</td>
<td>[U]</td>
<td>0.5</td>
<td>0.7</td>
</tr>
<tr>
<td>CSP</td>
<td>[°C]</td>
<td>[U]</td>
<td>24</td>
<td>26</td>
</tr>
<tr>
<td>HSP</td>
<td>[°C]</td>
<td>[U]</td>
<td>20</td>
<td>22</td>
</tr>
<tr>
<td>HSPnight</td>
<td>[°C]</td>
<td>[U]</td>
<td>15</td>
<td>17</td>
</tr>
<tr>
<td>Tsupply</td>
<td>[°C]</td>
<td>[U]</td>
<td>16</td>
<td>18</td>
</tr>
</tbody>
</table>

The results of the uncertainty study are shown in *Table 6.3*. Each row represents a set of design parameter uncertainty, the undecided parameters are mentioned in the table. The outcome, which is expressed as a percentage of change for the PIs, is shown in the columns. The entry is solid filled when the set of design parameter uncertainty resulted in a percentage of change greater than the percent of change for the PI. The upper 25% ranges of variations are represented by the light grey colour. The longer the grey beam, the bigger the effect on the energy performance indicators. With the help of this matrix, a compact overview of the input uncertainty on different energy performance indicators can be given.

The first row of this matrix represents the uncertainty due to only the decided parameter uncertainty. This uncertainty is of particular interest in the final design stage, wherein it is assumed that all the design decisions have been made. The decided parameter uncertainty had the biggest impact on the annual cooling demand, with an average variation of 12%.

As a result of both decided and investigated undecided parameter uncertainty, the average variation in cooling energy can be as low as 12% (for the decided parameter uncertainty) and as high as 130%. The cooling energy demand is the most sensitive performance indicator to the variation in decided design parameters, when compared to heating demand and total energy. For each set of design parameters the
Table 6.3. Results of uncertainty analyses on respectively heating, cooling, and energy demand for Level III considering the office case study building. The results are expressed as a percentage of variation in energy demand. The set of undecided design parameters are shown on the two right-most columns of this table, where the second column is added to the first column. The first row of this matrix represents the uncertainty due to only the decided parameter uncertainty. This uncertainty is of particular interest in the final design stage. The number of scenarios varied from 60 till 200 depending on the set of undecided parameters.

<table>
<thead>
<tr>
<th>Decided parameter uncertainty</th>
<th>Uncertainty on Annual Heating Energy demand [%]</th>
<th>Uncertainty on Annual Cooling Energy demand [%]</th>
<th>Uncertainty on Total Annual Energy Demand [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>5 10 15 20 25 30 35 40 45</td>
<td>10 20 30 40 50 60 70 80 90 100 110 120 130 140 150 250 350 450</td>
<td>5 10 15 20 25 30 35 40 45</td>
</tr>
<tr>
<td>WWNR North [20%]</td>
<td>(\mu = 2.0)</td>
<td>(\mu = 1.6)</td>
<td>(\mu = 2.4)</td>
</tr>
<tr>
<td>WWNR South [20%]</td>
<td>(\mu = 2.5)</td>
<td>(\mu = 1.3)</td>
<td>(\mu = 2.2)</td>
</tr>
<tr>
<td>WWER East [20%]</td>
<td>(\mu = 5.7)</td>
<td>(\mu = 11.9)</td>
<td>(\mu = 5.8)</td>
</tr>
<tr>
<td>WWER West [20%]</td>
<td>(\mu = 2.7)</td>
<td>(\mu = 11.1)</td>
<td>(\mu = 2.7)</td>
</tr>
<tr>
<td>WWER S+N [20%]</td>
<td>(\mu = 2.7)</td>
<td>(\mu = 3.3)</td>
<td>(\mu = 4.8)</td>
</tr>
<tr>
<td>WWER all [20%]</td>
<td>(\mu = 6.4)</td>
<td>(\mu = 7.0)</td>
<td>(\mu = 7.5)</td>
</tr>
<tr>
<td>External shading coefficient [20%]</td>
<td>(\mu = 2.4)</td>
<td>(\mu = 2.6)</td>
<td>(\mu = 3.6)</td>
</tr>
<tr>
<td>WWER South [20%] +SC [20%]</td>
<td>(\mu = 6.6)</td>
<td>(\mu = 5.8)</td>
<td>(\mu = 4.5)</td>
</tr>
<tr>
<td>WWER SS [20%] +SC [20%]</td>
<td>(\mu = 7.0)</td>
<td>(\mu = 9.2)</td>
<td>(\mu = 7.6)</td>
</tr>
<tr>
<td>WWER all [20%]</td>
<td>(\mu = 8.8)</td>
<td>(\mu = 8.6)</td>
<td>(\mu = 5.6)</td>
</tr>
<tr>
<td>R-value wall [20%]</td>
<td>(\mu = 3.9)</td>
<td>(\mu = 3.3)</td>
<td>(\mu = 4.8)</td>
</tr>
<tr>
<td>WWER North [20%]</td>
<td>(\mu = 8.4)</td>
<td>(\mu = 13.9)</td>
<td>(\mu = 8.0)</td>
</tr>
<tr>
<td>WWER South [20%]</td>
<td>(\mu = 8.4)</td>
<td>(\mu = 13.9)</td>
<td>(\mu = 6.1)</td>
</tr>
<tr>
<td>WWER S+N [20%]</td>
<td>(\mu = 5.5)</td>
<td>(\mu = 21.0)</td>
<td>(\mu = 7.4)</td>
</tr>
<tr>
<td>WWER [20%]</td>
<td>(\mu = 6.6)</td>
<td>(\mu = 25.0)</td>
<td>(\mu = 6.7)</td>
</tr>
<tr>
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<td>(\mu = 4.8)</td>
<td>(\mu = 3.9)</td>
<td>(\mu = 7.8)</td>
</tr>
<tr>
<td>Wall [20%]</td>
<td>(\mu = 8.1)</td>
<td>(\mu = 2.4)</td>
<td>(\mu = 4.8)</td>
</tr>
<tr>
<td>WWER North [20%]</td>
<td>(\mu = 14.8)</td>
<td>(\mu = 14.5)</td>
<td>(\mu = 15.8)</td>
</tr>
<tr>
<td>WWER South [20%]</td>
<td>(\mu = 7.9)</td>
<td>(\mu = 4.0)</td>
<td>(\mu = 7.6)</td>
</tr>
<tr>
<td>WWER + Rowall [20%]</td>
<td>(\mu = 7.9)</td>
<td>(\mu = 4.0)</td>
<td>(\mu = 7.6)</td>
</tr>
<tr>
<td>WWER + Roof [20%]</td>
<td>(\mu = 19.4)</td>
<td>(\mu = 29.5)</td>
<td>(\mu = 7.0)</td>
</tr>
<tr>
<td>WWER + Rowall [20%]</td>
<td>(\mu = 20.8)</td>
<td>(\mu = 30.2)</td>
<td>(\mu = 6.1)</td>
</tr>
<tr>
<td>WWER + Rowall [20%]</td>
<td>(\mu = 3.5)</td>
<td>(\mu = 2.0)</td>
<td>(\mu = 5.4)</td>
</tr>
<tr>
<td>WWER North + Recall [20%]</td>
<td>(\mu = 5.2)</td>
<td>(\mu = 2.0)</td>
<td>(\mu = 7.6)</td>
</tr>
<tr>
<td>WWER South + Rowall [20%]</td>
<td>(\mu = 5.5)</td>
<td>(\mu = 2.0)</td>
<td>(\mu = 7.6)</td>
</tr>
<tr>
<td>WWER S+N Recall [20%]</td>
<td>(\mu = 5.5)</td>
<td>(\mu = 2.0)</td>
<td>(\mu = 7.6)</td>
</tr>
<tr>
<td>WWER north [20%]</td>
<td>(\mu = 8.8)</td>
<td>(\mu = 12.3)</td>
<td>(\mu = 6.1)</td>
</tr>
<tr>
<td>WWER South [20%]</td>
<td>(\mu = 7.4)</td>
<td>(\mu = 9.5)</td>
<td>(\mu = 5.2)</td>
</tr>
<tr>
<td>WWER + Rowall [20%]</td>
<td>(\mu = 7.4)</td>
<td>(\mu = 4.0)</td>
<td>(\mu = 5.2)</td>
</tr>
<tr>
<td>WWER + Rowall [20%]</td>
<td>(\mu = 2.3)</td>
<td>(\mu = 16.9)</td>
<td>(\mu = 4.8)</td>
</tr>
<tr>
<td>WWER north + Recall [20%]</td>
<td>(\mu = 13.8)</td>
<td>(\mu = 49.5)</td>
<td>(\mu = 13.8)</td>
</tr>
<tr>
<td>WWER, Recall [20%]</td>
<td>(\mu = 13.4)</td>
<td>(\mu = 41.3)</td>
<td>(\mu = 4.8)</td>
</tr>
<tr>
<td>Infiltration [20%]</td>
<td>(\mu = 13.7)</td>
<td>(\mu = 68.0)</td>
<td>(\mu = 9.5)</td>
</tr>
<tr>
<td>WWER North [20%]</td>
<td>(\mu = 15.7)</td>
<td>(\mu = 71.6)</td>
<td>(\mu = 8.1)</td>
</tr>
<tr>
<td>WWER South [20%]</td>
<td>(\mu = 15.8)</td>
<td>(\mu = 71.6)</td>
<td>(\mu = 9.1)</td>
</tr>
<tr>
<td>WWER S+N [20%]</td>
<td>(\mu = 15.8)</td>
<td>(\mu = 71.6)</td>
<td>(\mu = 11.1)</td>
</tr>
<tr>
<td>WWER all [20%]</td>
<td>(\mu = 15.8)</td>
<td>(\mu = 71.6)</td>
<td>(\mu = 11.1)</td>
</tr>
<tr>
<td>Glazing type (two glazing types)</td>
<td>(\mu = 15.8)</td>
<td>(\mu = 71.6)</td>
<td>(\mu = 11.1)</td>
</tr>
<tr>
<td>WWER S+N + SC [20%]</td>
<td>(\mu = 15.8)</td>
<td>(\mu = 71.6)</td>
<td>(\mu = 11.1)</td>
</tr>
<tr>
<td>WWER South + SC [20%]</td>
<td>(\mu = 15.8)</td>
<td>(\mu = 71.6)</td>
<td>(\mu = 11.1)</td>
</tr>
<tr>
<td>WWER S+N + SC [20%]</td>
<td>(\mu = 15.8)</td>
<td>(\mu = 71.6)</td>
<td>(\mu = 11.1)</td>
</tr>
<tr>
<td>WWER all + SC [20%]</td>
<td>(\mu = 15.8)</td>
<td>(\mu = 71.6)</td>
<td>(\mu = 11.1)</td>
</tr>
</tbody>
</table>

\(\mu\): Average value in variation [%]

- **Dark grey** represents 75% of the scenarios
- **Light grey** represents 25% of the scenarios
effect of input uncertainty on the cooling energy demand is higher: differences in average percentages up to 100% can be observed between cooling and heating energy demand. The glass type led to the highest variations for all the energy PIs. For both types double glazing is used, one glazing type has an insolation value of $U=1.4 \text{ W/m}^2\text{K}$ and a solar heat gain coefficient (SHGC) of 0.62, while the other type has a better insolation value of respectively $1.08 \text{ W/m}^2\text{K}$ and a SHGC of 0.49. According to the absolute values, heating is the dominated energy demand for the reference case study building for almost all the scenarios. Looking at the variation in total thermal energy demand the uncertainty remained within 35%. Compared to the cooling energy demand, this significantly smaller percentage of change revealed that the difference in cooling energy demand is (partly) compensated by the variation in heating energy demand. Hence, a decrease in heating energy demand will lead to a decrease in cooling and vice versa.

As shown in the flow-chart Figure 3.1., the overall prediction error must satisfy an acceptable level of error. This acceptable level could be specified by the client. If the pre-condition is not met, the results are considered to be too uncertain. Hence, design decisions have be taken upon those undecided design parameters. Therefore a sensitivity study is conducted to give quantitative information on which parameters are most influential. These results are presented in the next section.

### 6.3. SENSITIVITY STUDY

The results from the global sensitivity study are depicted in Figure 6.1. The sensitivity of undecided design parameters based on annual cooling and compared to annual heating energy demand can be seen on the left side of this figure. The negative value of the SRC means that a larger value of the parameter has a reduction effect on the result (annual heating or cooling energy demand). Thus, increasing the $g$-value of the glass has a positive effect on the heating energy demand, however a negative effect on the cooling energy demand. Increasing the thermal resistance by 20% change of its base value (for the wall the base value is $5.5\text{m}^2\text{K/W}$) has a small effect on the energy demand.

The results of the sensitivity analysis confirm the results of the uncertainty analysis; Figure 6.1. shows the highest SRC for the annual cooling energy demand for the $g$-value, whereas Table 6.3 indicates the
highest variation for the sets in which the glass type is not yet decided. The results of the individual sensitivities in which the remaining parameters are not changed can be found in the Appendix A.

The right side of Figure 6.1. shows the sensitivity of peak heating and cooling load for the undecided design parameters. For the peak loads, the g-value and the shading coefficient (SC) have the largest influence on the heating and cooling energy demand. Although a significant lower regression coefficient for the peak heating load is found for the g-value of the glass. For the cooling peak loads, the main factor is the g-value with a strong positive correlation, followed by the shading coefficient which has a negative correlation.

6.4. MODEL SELECTION IN DECISION SUPPORT

6.4.1. Performance comparison of two design alternatives

The design question for choosing among design alternatives in early design stages, should take into consideration the effect of how the building design will evolve (e.g. the undecided design parameters). Therefore, the results are presented with a bandwidth of reliability rather than given a single value for both designs. The results of the heating load for Level II and Level III are depicted in the boxplots of Figure 6.2 for two designs, respectively design A and design B. The two designs differ from each other with respect to glass type, window surface area, and the resistance of the thermal envelope. In the bottom of this figure the boxplots for the cooling loads for Level II (left) and Level III (right) are shown. Note that scales are not shown on the boxplots, because we want the relative differences between the two options stand out, rather than the actual values for heating and cooling energy demand. From a decision standpoint, both Level II and Level III suggest that option B is the preferred one in terms of heating and cooling energy demand.

Table 6.4. presents the mean and standard deviation for the absolute values of both levels. The heating loads showed a fair agreement, however, a large disagreement can be found for the cooling load. Except

<table>
<thead>
<tr>
<th>Level</th>
<th>Heating Load [kWh/m²]</th>
<th>Cooling Load [kWh/m²]</th>
<th>Energy [kWh/m²]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Level II A B A B</td>
<td>Level II A B A B</td>
<td>Level II A B A B</td>
</tr>
<tr>
<td>Design</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>29.5 18.0 26.0 14.9</td>
<td>25.7 23.6 11.0 4.5</td>
<td>55.2 41.6 10.0 5.2</td>
</tr>
<tr>
<td>Std</td>
<td>0.82 0.67 0.56 0.17</td>
<td>0.59 0.80 0.86 0.17</td>
<td>0.77 0.45 0.27 0.06</td>
</tr>
</tbody>
</table>

Figure 6.2. Box plots of design A and B for respectively Level II (left side) and Level III (right) for annual heating and cooling energy demand.
for the calculation of the cooling load of Level II, a smaller deviation is found for design B. This could be explained by the better glass performance of option B, thus, the uncertainty of the window area has less influence on heating and cooling energy demand.

6.4.2. Performance comparison for sizing and selecting HVAC system

**Sizing HVAC system**

For sizing systems, the simulation outputs of interest are the peak loads and the profiles of heating and cooling loads. These load profiles are represented by a load duration curve, in which the relationship between the capacity requirements and capacity utilization in hours of a year is given. This curve provides information on the number of hours of the year at which the load is at or above a given peak load. The area under the curve corresponds to the annual heating and cooling requirement.

Figure 6.3. shows the year load duration curves for design option B for the both levels. According to the year duration curves, the cooling peak load obtained from Level II is almost two times higher compared to the dynamic simulation. The Level II-tool overestimated especially the cooling energy requirements. Hence, the equipment size and capacity required for the system will differ according to these results.

**Selecting HVAC system**

The three HVAC configurations as described in section 4.4 are modelled in the three complexity levels. For this purpose Level IV was involved in the selection process for system design. As mentioned earlier, this level simultaneously simulated the building and the secondary HVAC systems and thus differs from the decoupled approach (Level III).

Figure 6.4. shows the comparison between the three HVAC-systems for Level II, III, and IV. The interval between the horizontal grid lines is 5 kWh/m² for each level. Very different absolute values are observed between Level II and the higher complexity levels. The boxplots of HVAC conf. 2 and 3 partly overlap for Level II. Based on these results this level does not support a design decision as those two configurations are very similar in terms of energy performance. In contrast, the results from Level III and IV showed that configuration 3 is the most efficient energy system. Implementing indirect adiabatic cooling resulted in a significant reduction of the total energy demand by approximately 31%
Results of the model complexity simulations

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Figure 6.4. Comparison between three HVAC configurations for complexity levels II, III, and IV for total energy demand.

For Level III and 28% for Level IV. Therefore, both models are equivalent from the perspective of decision making. Configuration 1, including twin coil heat recovery, resulted in the highest peak loads and total energy demands for all the levels of model complexities.

Table 6.5. presents the absolute values for the different HVAC configurations. Note that the rule of thumb values (Level I) is added to the comparison, given the minimum and maximum value for the heating and cooling energy demand of Dutch office buildings. The rule of thumb values indicate higher values for the cooling energy demand in comparison with Level III and IV. The minimum values stated by the rule-of-thumb method showed a fairly good disagreement with HVAC configuration 2 of Level IV.

Table 6.5. Results of the three HVAC configuration for the complexity levels II, III, and IV in comparison with rule-of-thumb values for office building (Level I).

For HVAC configuration 1, the outcome for the monthly result for the decoupled and fully-integrated approach are shown in Figure 6.5. A distinction is made between system heating (i.e. the local heating demand which is provided by the radiator) and the heating demand required for the air handling unit (CAV system). The monthly cooling energy demand predicted by both levels is quite similar for all months. The monthly heating (thermal and system) requirements showed the largest differences between the coupling methods. For HVAC configuration 1 the differences can go up to 50%. The heating energy demand required for the air handling is higher for Level IV in comparison with Level III. However, the yearly total heating energy demand calculated by the decoupled approach is always lower in comparison with the integrated tool, due to the perfect match between the supply and demand side.

As can be concluded from Figure 6.4. and Figure 6.5., the monthly profile showed a similar trend and no large discrepancies between the coupling methods for the peak loads were found. The heating and cooling peak loads remained within the range of 16% for all the HVAC configurations. The monthly comparison for heating and cooling energy demand for HVAC configuration 2 and 3, can be found in Appendix B.
6.5. SCENARIO UNCERTAINTY ANALYSIS

For the three HVAC configurations the effect of scenario uncertainty is assessed; the results are depicted in Figure 6.6. The energy demand is composed of building energy demand and the heating and cooling energy for the HVAC system. This figure confirms that the amount of energy required by the HVAC system does not equate the building energy.

Figure 6.5. Monthly comparison between decoupled approach (Level III) and coupled approach (Level IV) for HVAC configurations 1, including twin-coil heat recovery.

Figure 6.6. Influence of scenario uncertainty on heating energy demand (top) and cooling energy demand (bottom) for the different HVAC configurations. The scenario uncertainty is expressed as a percentage of change for the three internal heat sources (equipment, lighting, and people).
Results of the model complexity simulations

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From the barplots it can be concluded that the simplified tool (Level II) is most sensitive to the internal heat gains. This is contrary to Level IV, in which the cooling needs are quite insensitive to changes in the internal heat gains. This insensitivity can be explained by the fact that the cooling energy demand calculated by Level IV is dependent on the airflow rate and supply temperatures, which are not affected by the internal heat gains. For Level II and III the cooling energy requirement is also dependent on the internal heat gains.

Figure 6.7. shows the standardized regression coefficient for the heating and cooling setpoints on the annual energy demand and the peak loads. This figure shows the heating setpoint as variable having the biggest importance on the uncertainty of the annual heating. Except for the g-value, the effect on heating and energy demand is larger for the setpoints in comparison with the design parameters, as was illustrated in Figure 6.1.

Figure 6.6. Standardized regression coefficient of heating and cooling setpoints on annual heating and cooling demand (right) and heating and cooling peak loads (left).

To assess the risk of overheating when internal heat gains changes, the number of hours in which the zone temperature is above 24.5 and 25.5 °C are counted for Level IV. Table 6.6. provides the results of the zone temperature deviations and number of hours due to the increasing internal heat gains. As a consequence of the 20% increase in internal heat production, the zone temperature shows a maximum deviation of 1.66 °C during occupied hours. A higher deviation is found for the circulation area, respectively 2.50 °C. Despite these deviations, a sufficient level of thermal comfort is achieved. The zone temperature is for only 37 hours above 25.5°C. In addition, for all zones the number of hours when the temperature is above 24.5 is less than 100

Table 6.6. Exceeding hours and temperature increase as a result of increasing the internal heat production by respectively 10 % and 20%.

<table>
<thead>
<tr>
<th>Zone</th>
<th>T &gt; 24.5°</th>
<th>T &gt; 25.5°</th>
<th>T &gt; 24.5°</th>
<th>T &gt; 25.5°</th>
<th>ΔTmax [°C]</th>
</tr>
</thead>
<tbody>
<tr>
<td>A1</td>
<td>22</td>
<td>0</td>
<td>59</td>
<td>0</td>
<td>1.3</td>
</tr>
<tr>
<td>A2</td>
<td>2</td>
<td>0</td>
<td>10</td>
<td>0</td>
<td>1.0</td>
</tr>
<tr>
<td>A3</td>
<td>17</td>
<td>6</td>
<td>32</td>
<td>6</td>
<td>1.6</td>
</tr>
<tr>
<td>B1</td>
<td>20</td>
<td>0</td>
<td>51</td>
<td>0</td>
<td>1.6</td>
</tr>
<tr>
<td>B2</td>
<td>0</td>
<td>0</td>
<td>72</td>
<td>9</td>
<td>2.5</td>
</tr>
<tr>
<td>B3</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1.0</td>
</tr>
<tr>
<td>C1</td>
<td>42</td>
<td>4</td>
<td>97</td>
<td>6</td>
<td>1.2</td>
</tr>
<tr>
<td>C3</td>
<td>21</td>
<td>8</td>
<td>54</td>
<td>16</td>
<td>1.7</td>
</tr>
<tr>
<td>sum</td>
<td>124</td>
<td>18</td>
<td>375</td>
<td>37</td>
<td>-</td>
</tr>
</tbody>
</table>
7. DISCUSSION

7.1. THE PROPOSED FIT-FOR-PURPOSE MODEL COMPLEXITY

The novelty of this fit-for-purpose model selection strategy is that it quantifies the abstraction modelling error (AME) in order to identify the trade-off point between this error and the input uncertainty. This trade-off point helps to select the fit-for-purpose model complexity regarding building energy simulation. With the help of the matrix presented in Table 6.3 and the defined abstraction modelling error, the trade-off point between those two aspects can be identified for this specific case study.

For the case study building the AME of Level II is set on 58% for the cooling energy demand. In case the design parameter uncertainty of Level III is higher than the defined AME, the model complexity is considered to be too high given the required unknown or unavailable input data. The lower model complexity level would offer an equal overall prediction error. Whereas when the uncertainty on the outcome is lower than 58%, switching to a lower model complexity would decrease the overall prediction. Therefore, the Level III model complexity is preferred in terms of overall prediction error. In case the results are considered to be too uncertain i.e. the acceptable level of error is not met, the matrix in combination with the sensitivity analysis can be helpful to elucidate which parameters are most influential. These parameters have the highest priority to take design decisions in order to reduce the input uncertainty. Conversely, if is assumed that the overall prediction error is accepted, neither increasing the model complexity nor further assessment to reduce the input uncertainty is necessary.

An important point for finding the trade-off point is the choice of the ranges and distributions of the input parameters. The range of the undecided parameter uncertainty is based on, when possible, a fixed percentage of its base value. Although its base value complies with the latest Dutch building standards, the set and the distribution are not an adequate representation of undecided parameters. In addition, the set and range of undecided design parameters was not scientifically documented in contrary to the decided parameters. This makes the set and range arbitrary and leaves it up for discussion. More in-depth knowledge of realistic undecided design parameters and scientifically underpinned ranges of those parameters could improve the set and range which is used as an input for the uncertainty study. A further limitation of the uncertainty analysis is the fact that the investigated design parameters are independent of one another. No conditional probabilities are taken into account and thus the input parameters do not capture the likelihood of one parameter taking on a value given another parameter’s value. As such, the presented matrix may include unlikely combinations of decided and undecided parameters.
Although the abstraction modelling error is strongly related to the input parameters, it remained the same for the case study building. For other building types and even other office buildings types, the AME, and hence the trade-off point, would probably differ. Due to the strong correlation with the input parameters, it will be hard if not impossible to generalize an AME for a certain tool let alone a total complexity level.

### 7.2. DECISION SUPPORT FOR SELECTING AMONG DESIGN ALTERNATIVES

In terms of accuracy, Level II showed a large disagreement for the absolute values in comparison with the higher model complexity levels. In addition, this Level did not pass the BESTest, for case 600 and case 900. However, the presented results of Level II on alternative design comparison showed that Level II can be valid for the purpose of choosing among design alternatives, at least for the investigated designs. In case the boxplots do not overlap in Level II, this level can generally support the ‘right’ design decisions in terms of energy efficiency.

As illustrated in Figure 6.2, a higher level of model complexity does not affect the design decision. Furthermore, the boxplots visualize the effect of the undecided parameters uncertainty on the PIs. This provides useful information for designers on how much they can rely on the simulation prediction given the uncertainties from design parameters. A limitation of the presented comparison is that it is obvious that design B is the most preferable design solution given the better thermal resistance and glass performance. In addition, the selection between a respectively energy-efficient and highly energy efficient design is probably not a realistic building design question.

### 7.3. DECISION SUPPORT FOR SIZING AND SELECTING HVAC SYSTEMS

Comparing HVAC configuration at different levels of model complexity greatly increased our understanding of the influence of model complexity levels on design decision-making. A modelling error in the efficiency of the heat recovery unit (hru) of Level II was detected. Increasing the energy-efficiency of the hru resulted in a small increase in heating energy demand for only Level II while the demand should be decreased or at least stay constant. The absolute values calculated by Level II are too far apart from the higher model complexity levels. As elaborated earlier, Level II omits key processes, such as thermal capacity, that influence building energy demand resulting in large discrepancies for the absolute values.

Turning back to the results of the HVAC system, a fair agreement between the decoupled and fully integrated approach was found for the yearly and monthly values. For all the configurations, the peak loads values remained within 16% and the yearly values for cooling energy demand remained within 20%. The monthly heating energy predictions showed the largest discrepancies, up to 50%, between the coupling approaches, this could be explained by the following reasons:

- Level III assumes an ideal load system with perfect control, no time lags, and unlimited power
for each thermal zone is used. Subsequently, this “ideal” system only results in ‘gross’ energy requirements, as it ignores the dynamic interaction between the demand and supply side. On the contrary, in the fully integrated complexity approach this interaction between system and building is modelled. The radiator in the case study building was monitored by a zonal thermostat, controlling the hot water flow rate to the radiators. The heat supplied will not perfectly match the heating demand. In addition, the amount of time that the radiator will remain “on” once it has turned on is set on 20 minutes. Consequently, this is associated with a certain mismatch between the demand and supply. Although we use the term mismatch, for a building with a radiator system discrepancy between heating demand and supply are hardly to overcome. In addition, Level IV used a time step of 5 minutes. Each time step TRNSYS simultaneously solve the algebraic and differential equations comprising the system model. For Level III a time step of one hour was used for calculating the system energy demand. The differences in time step can be attributed to the discrepancies.

- Despite the fact that Level III contains almost the same input parameters as encountered in the HVAC component formulation of TRNSYS, the complexity of the HVAC simulation is simplified. Firstly, the variability of the supply temperature is ignored in the current situation of the decoupled approach in contrary a heating/cooling curve for the supply temperature is applied for Level IV. To isolate the effect of the zonal supply variability we conduct another case for a fixed supply temperature of Level IV. The results confirm our intuition that the differences between the two approaches became smaller when the supply temperature is fixed for Level IV. Secondly, the decoupled approach uses a fixed amount of heat losses by the fan and motor on the airstream, while in Level III the heat added to the airstream is variable as it depends on the mass flow rates, the pressure of the air, relative humidity, and fan efficiency. As a result, the delta outlet air temperature due to fan losses varied between 0,2°C to 1,5°C for the selected fan. Finally, the calculation of the latent energy due to slightly different humidity ratios could cause discrepancy of the cooling requirements between the two modelling approaches. For example, Level III either uses a minimum humidity ratio or the outdoor humidity ratio, while in Level IV the effective saturation humidity ratio is determined found with psychometric data.

In this research, all the HVAC configurations have a constant air volume (CAV) system, which is for newly built multi-zone office buildings somewhat rare due to the high fan energy. In comparison with variable air volume (VAV) system, a CAV system has less dynamic interaction with the building as the air flow volume in the central AHU is constant. Whereas the VAV system varies its supply air volume rate to meet varying zone loads in the building. For VAV systems it can be argued that the difference between the fully integrated and decoupled approach will be higher, as the zonal variability of the air distributions are presumably not well captured in the decoupled approach. For water-based systems such as radiant floor heating, the decoupled approach could even lose its applicability [52]. Further research could study these types of systems to investigate if the model complexity will have influence on the design decisions.
The work presented in this thesis uncovered the potential of the developed framework for selecting the fit-for-purpose model complexity by quantifying the abstraction modelling error. In this way, a trade-off between input uncertainty and error can be found, which is useful for the selection of the fit-for-purpose model complexity. Uncertainty and sensitivity analyses are used as a tool in order to find the fit-for-purpose model complexity. The uncertainty analysis quantifies the uncertainty that arise from the undecided and decided design parameters. A sensitivity study is useful for elucidating the parameters that are most influential. These parameters have the highest priority to take design decisions in order to reduce the input uncertainty.

An essential first step in this framework is to clarify for which purpose the simulation is needed. Some purposes immediately exclude the use of some complexity levels and tools. Despite this exclusion the modeler will have a suite of tools from which to choose. The main contribution of this work is that it compares models at different levels of complexity and offers insight how these levels affect the decisions related to building design. The preliminary results showed that Level II can provide guidance for selecting among building design alternatives. Caution should be taken in interpreting the results from comparative analyses of building design with different thermal capacity. Because of the effect of thermal capacity on the energy performance is not considered in Level II. In addition, the design decision for selecting the HVAC system differs from the higher complexity levels due to the inability of modelling indirect adiabatic cooling. From the presented case-study results we conclude that Level II is inappropriate for sizing systems, as the energy requirements and the cooling peak loads are significant higher compared to TRNSYS.

The results of the three HVAC configuration for the decoupled (Level III) and fully integrated (Level IV) modelling approach showed a good agreement based on the monthly profiles and yearly values, as the yearly difference remained within 20%. Similar savings of the total energy demand by implementing indirect adiabatic cooling was found for both modelling approaches. Both levels suggest the same system design decision by the criteria of both cooling and heating energy demand.

The proposed framework provides a good starting point for finding the fit-for-purpose model complexity, however, it leaves unanswered which tool has to be selected for a given purpose. As every case has another set of uncertainties and every tool another set of abstraction modelling error. Future research is needed to further develop the methodology, especially concerning the generalizability of a models abstraction error. More in-depth knowledge about the relationship between the level of model complexity and the model performances predictions could improve the quantification of the abstraction error. In further
Conclusions

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research, it would be advisable to have real measurement data from the case study. This would help tremendously in the validation process of the model and to give answer on which model is the most accurate representation of the building.

Our study has been limited to a Dutch office building equipped with CAV system. However for newly built multi-zone office buildings a variable air volume (VAV) is more common due to fan energy savings potential. For VAV systems the differences between the fully integrated and decoupled approach may change and influence design decisions, making the motivation for this study become more pronounced. Further research could study these types of systems to investigate if the model complexity will have influence on the design decisions. A follow-up study could be extended with the simulation of primary systems that generate heating/cooling energy such as boilers and chillers. The primary system was out of scope for this present research. It will also be interesting to take into consideration the prediction of electricity demands for auxiliary equipment in order to investigate if the model complexity affects the choice of the HVAC system that has the best overall performance.
REFERENCES


References


[54] CODYBA software, INSA Lyon, version 6.50.


APPENDIX A

SENSITIVITY STUDY

The local sensitivity study is conducted to give insight in the individual sensitivity, meaning the influence on energy predictions in each individual input parameter. The input ranges and distribution for the individual sensitivity analysis are found in Table A.1. Slightly different input values are adopted for the sensitivity study in comparison with the uncertainty analysis. Figure A.1.-A.6 show the effect of each parameter on respectively annual heating, cooling, and energy demand. All parameters were kept at their base values, except for the parameter of interest. It is important to note that the apparent sensitivity is highly dependent on the range.

Table A.1  Input ranges and distribution for the sensitivity study:

<table>
<thead>
<tr>
<th>Input sensitivity study</th>
<th>Unit</th>
<th>Distr.</th>
<th>Min</th>
<th>Max</th>
<th>Base</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rcvalue wall</td>
<td>[m² K/W] [U]</td>
<td>5</td>
<td>7</td>
<td>5</td>
<td></td>
</tr>
<tr>
<td>Rc value roof</td>
<td>[m² K/W] [U]</td>
<td>6</td>
<td>8</td>
<td>6</td>
<td></td>
</tr>
<tr>
<td>Rcvalue roof</td>
<td>[m² K/W] [U]</td>
<td>6</td>
<td>9</td>
<td>6</td>
<td></td>
</tr>
<tr>
<td>North</td>
<td>[m²] [U]</td>
<td>26</td>
<td>39</td>
<td>26</td>
<td></td>
</tr>
<tr>
<td>South</td>
<td>[m²] [U]</td>
<td>26</td>
<td>39</td>
<td>28</td>
<td></td>
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<tr>
<td>Window area</td>
<td>[m²] [U]</td>
<td>3</td>
<td>6</td>
<td>6</td>
<td></td>
</tr>
<tr>
<td>East</td>
<td>[m²] [U]</td>
<td>3</td>
<td>6</td>
<td>5</td>
<td></td>
</tr>
<tr>
<td>West</td>
<td>[m²] [U]</td>
<td>3</td>
<td>6</td>
<td>5</td>
<td></td>
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<tr>
<td>Infiltration</td>
<td>[ACH] [U]</td>
<td>0,2</td>
<td>0,5</td>
<td>0,5</td>
<td></td>
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<tr>
<td>Uvalue glass</td>
<td>[W/m²K] [U]</td>
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<td>1,4</td>
<td>1,4</td>
<td></td>
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<tr>
<td>Gvalue glass</td>
<td>[-] [U]</td>
<td>0,2</td>
<td>0,6</td>
<td>0,6</td>
<td></td>
</tr>
<tr>
<td>Shading coefficient</td>
<td>[-] [U]</td>
<td>0,5</td>
<td>0,7</td>
<td>-</td>
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<tr>
<td>CSP</td>
<td>[ºC] [U]</td>
<td>24</td>
<td>26</td>
<td>24</td>
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</tr>
<tr>
<td>HSP</td>
<td>[ºC] [U]</td>
<td>20</td>
<td>22</td>
<td>21</td>
<td></td>
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<tr>
<td>HSPnight</td>
<td>[ºC] [U]</td>
<td>15</td>
<td>17</td>
<td>17</td>
<td></td>
</tr>
<tr>
<td>Tsupply</td>
<td>[ºC] [U]</td>
<td>16</td>
<td>19</td>
<td>17</td>
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</table>
Figure A.1. Influence of individual parameters related to the window on heating energy demand for the quasi-steady state model (Level II) and TRNSYS (referred as Level IV in the figure) expressed as percentage of change.

Figure A.2. Influence of individual parameters on thermal cooling energy demand for the quasi-steady state model (Level II) and TRNSYS (referred as Level IV in the figure) expressed as percentage of change.

Figure A.3. Influence of individual parameters on thermal energy demand for the quasi-steady state model (Level II) and TRNSYS (referred as Level IV in the figure).
Figure A.4. Influence of individual design parameters on heating energy demand for the quasi-steady state model (Level II) and TRNSYS (referred as Level IV in the figure) expressed as percentage of change.

Figure A.5. Influence of individual design parameters on cooling energy demand for the quasi-steady state model (Level II) and TRNSYS (referred as Level IV in the figure) expressed as percentage of change.

Figure A.6. Influence of individual design parameters on thermal energy demand for the quasi-steady state model (Level II) and TRNSYS (referred as Level IV in the figure).
The top five main parameters that are most significant for both levels are listed in Table A.2. This table also quantifies the sensitivity of each parameter according to the following equation [53]:

$$\left( \frac{\Delta OP}{\Delta IP} \right) + \left( \frac{OP}{IP} \right) \quad (A1)$$

where $\Delta OP$ is the difference in output values (predicted energy use) for the extreme values of each parameter, $\Delta IP$ is the difference in input values (extreme parameter values), and $\overline{OP}$ and $\overline{IP}$ are the mean output and input values.

Table A.2  Top five most sensitive parameters on energy demand and their sensitivity according to equation A1.

<table>
<thead>
<tr>
<th>Design parameter</th>
<th>Sensitivity</th>
<th>Design parameter</th>
<th>Sensitivity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Infiltration</td>
<td>0.29</td>
<td>Heating setpoint</td>
<td>3.18</td>
</tr>
<tr>
<td>South facing window type</td>
<td>0.19/0.47</td>
<td>Infiltration</td>
<td>0.23</td>
</tr>
<tr>
<td>(Uvalue/Gvalue)</td>
<td></td>
<td>Shading coefficient</td>
<td>1.07</td>
</tr>
<tr>
<td>Window area south facade</td>
<td>0.34</td>
<td>South facing window type</td>
<td>0.16/0.26</td>
</tr>
<tr>
<td>Supply temperature</td>
<td>2.78</td>
<td>(Uvalue/G value)</td>
<td>0.26</td>
</tr>
<tr>
<td>Heating setpoint</td>
<td>2.98</td>
<td>Window area south facade</td>
<td>0.34</td>
</tr>
</tbody>
</table>

Apart from the shading coefficient, the top five of most signficant parameters consists of the same parameters for both levels. The result of the sensitivity study indicates the important role of infiltration in energy performance prediction, having the largest variation in heating energy demand. This is primarily because of the large input range, varying from 0.15 to 0.5 ACH for buildings air tightness. Variations in annual thermal energy demand up to 35% are observed for both levels. This indicates a strong need for careful estimation and modelling of infiltration. However, a more accurate way to predict the infiltration characteristics can only performed after construction with a blower door test [54].

The total energy demand is quite sensitive to heating and cooling setpoints especially for the TRNSYS model, as indicated by Figure A.4 and A.5. The difference in sensitivity is partly owing to the fact that the Level II does not consider the conductive heat transfer and the storage of solar gains. If the temperature is allowed to float within a larger temperature range the temperature difference across the envelope will be lower on average, translating to less conductive heat transfer. In addition, sensible energy can be effectively stored in the building construction for as long as a day, thus bridging the gap between sunny days.

The glazing type for the south and north facing window is particularly critical because of its large area. The window to wall ratio and glazing type on the south facing window has most impact on the energy demand, as expected. Interesting, the results of both levels indicate another glass type as most beneficial in terms of energy performance. However, both levels indicate that a higher g-value on north-facing windows is most beneficial in terms of energy performance. Insulation levels – particularly the roof and floor – have a relatively insignificant impact on the energy performance.
While these results are certainly indicative of the sensitivity of performance to each of the parameters, it is important to note that they are dependent on the variation in the model's parameters [22][35]. A parameter that would appear to be insignificant from this analysis is not necessarily insignificant in the context of the other parameters or maybe even other buildings. Its inclusion can be essential if this parameter exhibits strong interactions with one or more other parameters. Thus, while the results of such a sensitivity analysis sometimes suggested that a parameter have a negligible effect on the PI, this should be exercised with caution [55].
APPENDIX B

Monthly comparison of HVAC configuration 2 and 3

Figure B.1. shows the monthly energy demand for heating and cooling respectively for HVAC configuration 2, including cross flow heat exchanger. As mentioned before, a distinction is made between the heating energy demand required for heating the supply air (CAV system) and the local heating, for this case study building the heat supplied by the radiator. The monthly profiles are reasonable and comparable for the decoupled and coupled simulation approach. However, in absolute monthly values differences up to 30% in heating are observed. However the yearly and peak loads are within the range of 20%.

Figure B.2. illustrates the results for HVAC configuration 3, including indirect adiabatic cooling. This configuration resulted in the largest differences in terms of monthly cooling values between the two levels. For all the months the predicted heating energy demand by Level IV is higher in comparison with Level III for this configuration. This trend was previously observed for HVAC configuration 1. In general, the monthly cooling energy demand is reasonable comparable.

Figure B.1. The monthly heating and cooling energy demand calculated by Level III (decoupled approach) and Level IV (coupled approach) for HVAC configuration 2, including cross heat flow exchanger.
From Figure B.1. and Figure B.2. it can be concluded that the HVAC configuration has the largest impact on the heating energy demand required for the air handling unit, as expected. The heating energy demand required for the twin coil unit is for both complexity levels more than three times higher than for heat recovery method including indirect adiabatic cooling (HVAC configuration 3). From a decision point of view, both levels suggest HVAC configuration 3 as the preferred one.

Figure B.3. shows the effect of increasing the internal heat production of each zone by respectively -20%, -10%, 10%, and 20% from its base value on the peak loads on HVAC configuration 3 for the different complexity levels. The heating peak loads of Level III and Level IV showed a good agreement. For Level II higher peak loads for both cooling and heating are observed in comparison with the higher model complexity levels.

Figure B.3. Impact of increasing the internal heat production by -20%, -10%, 10%, and 20% from its base values on the peak loads for the three complexity levels.