Predicting the Energy Performance of Buildings

A Method using Probabilistic Risk Analysis for Data-driven Decision-support

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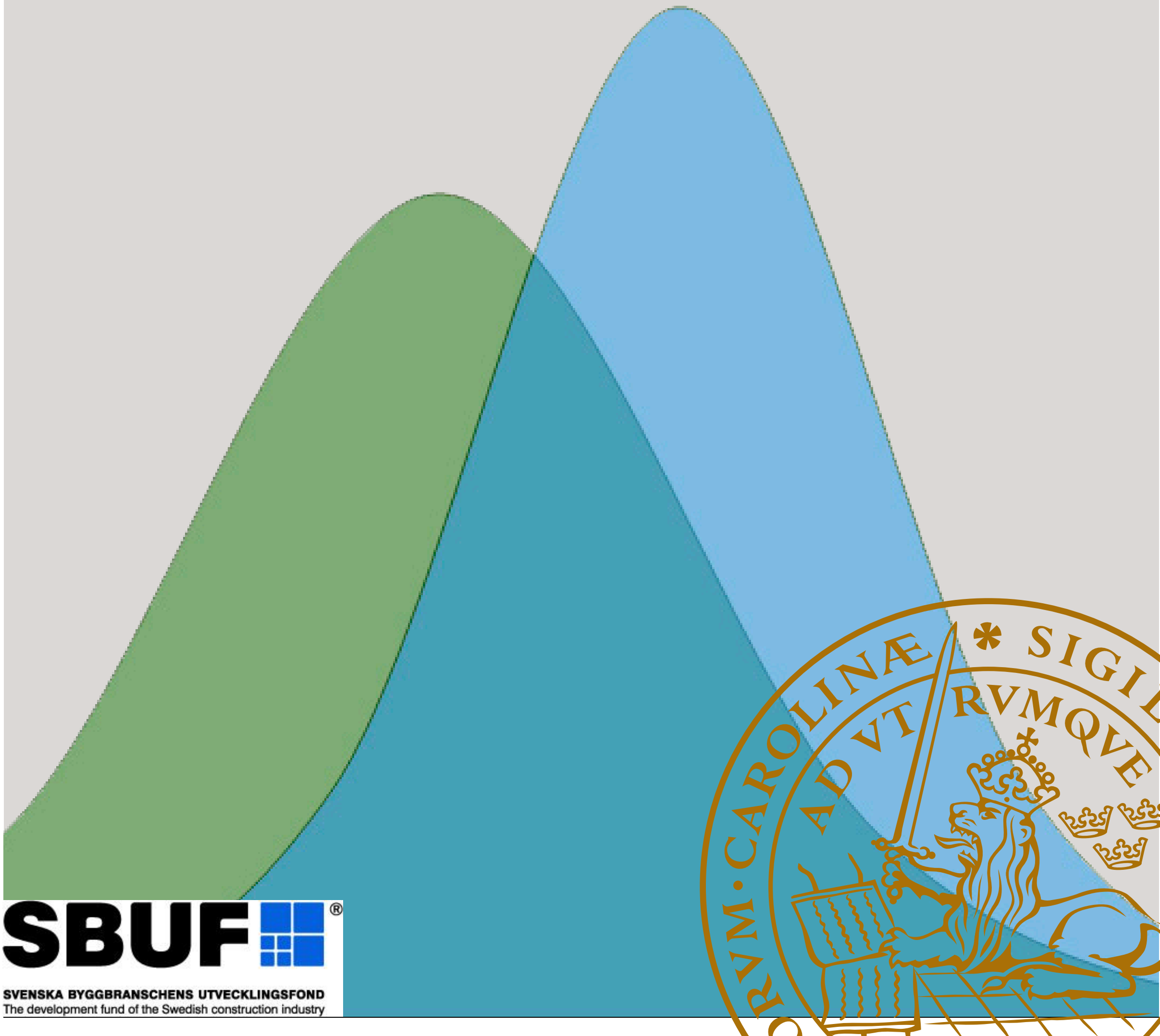
BUILDING AND ENVIRONMENTAL TECHNOLOGY | LTH | LUND UNIVERSITY



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Abstract

As most countries worldwide continue to mitigate climate change, one area of focus is a building's energy efficiency. Buildings currently account for approximately 40 per cent of the total energy use in the European Union. One solution for reducing the energy demand from buildings is by continually implementing more stringent building regulations. Consequently, the importance of accurate and efficient building performance simulations to predict the energy performance of a building design increases with more stringent regulation reducing the margin of error. However, a performance gap exists between the predicted energy performance and a building's actual energy performance.

This research uses the concept of risk, which consists of probability and consequence, to bridge the knowledge gap and explain and predict the energy performance gap. This research aimed to develop and test a method for using a predictive model to quantify a building design's risk level and evaluate design options. The developed method uses probabilistic risk analysis for predicting the energy performance of buildings resulting in a data-driven decision-support when deciding the building design. The studies used the research strategy of case studies to test the method and compared the outcome against field measurements to validate the method and results.

The first study developed and tested an experimental version of the method in a case study, verifying the resulting predictive model against field measurements for the energy performance. The outcome showcased the potential with the developed method and several aspects needing further investigation and development. One aspect was regarding the accuracy of the predictive model, requiring further investigation into the data quality used as a basis for the model. However, the data resolution from the field measurements was coarse, reducing the analytical potential by only comparing the aggregated total. Thus, one purpose with the following case study was to increase the resolution to enable additional analytical comparisons and focused on the data quality. The study evaluated how various levels of data quality impact the predictive model's accuracy. The outcome showcased the importance of data quality and the impact on the predictive model. The other aspect was quantifying the consequences of not attaining the design criteria and developing the method to compare design options and support the decision-making process using a data-driven approach. The subsequent study evaluated how to develop the method to include optimising the building design. The implemented optimisation step compares design options and how the stakeholder viewpoints impact the analysis and models' scope when quantifying the risk. Also evaluated was how the selected design criteria impact a project's risk level. The evaluation illustrates how quantifying the risk level could improve the decision-making process, either when deciding on a building design or the design criterion to use.

The main findings from these studies were the benefits of implementing the probabilistic approach to quantify building designs' energy performance and how this could support the decision-makers during the design process while also clarifying the current limitations to overcome. With the outcomes of this project, the probabilistic methods for quantifying energy performance and consequences of decisions and how to apply them are more accessible to the building sector.

Key words energy efficiency, probabilistic, risk analysis, simulation, field measurements

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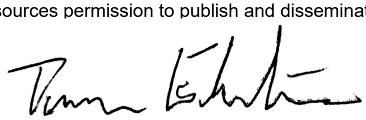
Signature  Date 2021-08-09

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MADE IN SWEDEN

Preface

Buildings, and the energy use of buildings, have been a topic of concern and interest for most parts of my life, from the annual piling of wood during the summer to heat the house during the winter in the wood-burning stove (an still ongoing tradition) to a summer job helping my father build post-and-plank timber houses (Bulhus). This interest later continued with studies at LTH, ending with a Master thesis at NCC focusing on thermal bridges in low-energy buildings, followed by working with building performance simulations at NCC since 2012.

Working at a large construction company as NCC allowed me to work on many projects, with various types and sizes of buildings, various complexity in systems and requirements, and multiple and changing stakeholders. Throughout the year's hundreds of buildings passed my computer screen, both existing and in the design phase, introducing me to the complexity of buildings, from a small bicycle workshop built inside an existing space next to a river with the external wall mostly underwater to high-rise high-performance residential buildings and most other types of buildings. Working on these projects gave me insight into a wide variety of solutions and when to apply them. In addition, from time to time, I encountered questions from stakeholders that I could not provide satisfactory answers to using the traditional methodology of building performance simulations, kindling an interest in improving the methodologies to enable better answers to important questions.

In 2014, this interest evolved to include PhD studies investigating cost-effective passive house renovations of single-family houses built during the 60s and 70s using building performance simulations, resulting in a Licentiate thesis. After almost one year of struggle to find a suitable continuation project and apply for the funding, the work continued in a different direction, focusing on the accuracy of the predicted energy performance from simulations using a probabilistic approach and how to use this different take on simulations to quantify the risk of deciding on a proposed design of a building for multiple stakeholders in a project. The result of this study is this thesis and the appended papers.

This has been an exciting, challenging, and fulfilling journey of diving deep into subjects of great personal interest. Thus, it is with some hesitation I write these last words because it means that my PhD studies are ending.

However, the knowledge and insights I've gained should provide for interesting future projects and collaborations.

I am grateful to the Development Fund of the Swedish Construction Industry (SBUF) and NCC AB for funding this doctoral thesis and giving me this opportunity for personal and professional development.

I would like to thank all my supervisors for their supervision, guidance, support, and thought-provoking discussions throughout the years. Since my research was conducted as an industrial PhD student from NCC within two different research groups, at two different departments and divisions within the Faculty of Engineering at Lund University, there have been several main- and co-supervisors throughout the years. The first part was conducted at the Division of Energy and Building Design at the Department of Architecture and Built Environment. The main supervisor was the late Åke Blomsterberg, and the co-supervisor was Ricardo Bernardo. From NCC, the industrial co-supervisor was first Kajsa Flodberg Munck, and during her parental leave, Mats Sihvonen took over the role. The second part was conducted at the Division of Building Physics, Department of Building and Environmental Technology. The main supervisor was Jesper Arfvidsson, with the co-supervisor Lars-Erik Harderup, and the industrial co-supervisor from NCC was Stephen Burke.

I also would like to thank all my colleagues at Energy and Building Design, Building Physics, and NCC and all members of the project groups and reference groups for the support and interesting discussions about the topics and problems arising within the studies.

Finally, I am deeply grateful to my family for their support throughout the years of conducting these studies.

Visby, August 2021

Abstract

As most countries worldwide continue to mitigate climate change, one area of focus is a building's energy efficiency. Buildings currently account for approximately 40 per cent of the total energy use in the European Union. One solution for reducing the energy demand from buildings is by continually implementing more stringent building regulations. Consequently, the importance of accurate and efficient building performance simulations to predict the energy performance of a building design increases with more stringent regulation reducing the margin of error. However, a performance gap exists between the predicted energy performance and a building's actual energy performance.

This research uses the concept of risk, which consists of probability and consequence, to bridge the knowledge gap and explain and predict the energy performance gap. This research aimed to develop and test a method for using a predictive model to quantify a building design's risk level and evaluate design options. The developed method uses probabilistic risk analysis for quantifying and predicting the energy performance of buildings, resulting in a data-driven decision-support when deciding the building design. The method was developed in steps, presented in several studies. The studies used the research strategy of case studies to test the method and compared the outcome against field measurements and was designed to develop, test, verify and validate the method.

One case study used the traditional deterministic approach for quantifying energy performance focused on identifying financially viable renovation packages to passive house level and comparing and optimising different energy performance levels for the building stock. The results showed the potential and limitations of the current method for building performance simulations in evaluating the design space and quantifying the energy performance and costs of different design options.

An explorative phase followed, identifying alternative methods and comparing these to the traditional deterministic approach based on the knowledge gained. Finally, qualitative methods were used to evaluate and discern when and for what purpose the alternative probabilistic methods might be advantageous to apply.

Based on the outcome of this work, the development of the probabilistic risk analysis method began, resulting in several studies focusing on different aspects of the method. The first study developed and tested an experimental version of the method in a case study, verifying the resulting predictive model against field

measurements for the energy performance. The outcome showcased the potential with the developed method and identified several aspects needing further investigation and development. One aspect was regarding the accuracy of the predictive model, requiring further investigation into the data quality used as a basis for the model. The other was how to quantify the consequences of not attaining the design criteria and develop the method to compare design options and support the decision-making process using a data-driven approach. However, the data resolution from the field measurements was coarse, reducing the analytical potential by only comparing the aggregated total.

Thus, one purpose with the following case study was to increase the resolution to enable additional analytical comparisons and focused on the data quality. The study evaluated how different levels of data quality impact the predictive model's accuracy. The outcome showcased the importance of data quality and the impact on the predictive model.

The subsequent study evaluated how to develop the method to include optimising the building design. The implemented optimisation step compares design options and how the stakeholder viewpoints impact the analysis and models' scope when quantifying the risk. Also evaluated was how the selected design criteria impact a project's risk level. The evaluation illustrates how quantifying the risk level could improve the decision-making process, either when deciding on a building design or the design criterion to use.

With the outcomes of this project, the probabilistic methods for quantifying energy performance and consequences of decisions and how to apply them are more accessible to the building sector. The main findings from these studies were the benefits of implementing the probabilistic approach to quantify building designs' energy performance and how this could support the decision-makers during the design process while also clarifying the current limitations to overcome. However, this method adds several new dimensions for data gathering, performing the simulations and analysis, and visualising and conveying the results using different plots. Furthermore, instead of providing a single value based on deterministic approaches for predicting the energy performance of a building design, the probabilistic approach provides a distribution of possible outcomes based on empiric data of uncertainties from which to quantify the probability of failure. Finally, the results also showed the importance and impact of data quality and a structured process for gathering data.

Sammanfattning

Byggnaders energieffektivitet är ett fokusområde i arbetet med att minska klimatförändringarna, då byggnader står för cirka 40 procent av den totala energianvändningen i Europeiska unionen. En lösning som tillämpas för att minska byggnaders energibehov är att ständigt införa strängare byggregler. Följaktligen ökar betydelsen av precisa och effektiva simuleringar för att kunna beräkna byggnaders framtida energianvändning. Det finns emellertid ofta en skillnad mellan den beräknade energiprestandan och en byggnads faktiska energiprestanda.

För att överbrygga kunskapsklyftan och förklara och förutsäga skillnaden i prestanda har denna studie använt begreppet risk, vilket består av sannolikhet och konsekvens. Syftet var att utveckla och testa en metod för att använda en prediktiv modell för att kvantifiera en byggnads risknivå och utvärdera olika designalternativ. Den utvecklade metoden använder probabilistisk riskanalys för att kvantifiera och förutsäga byggnaders energiprestanda vilket resulterar i ett datadrivet beslutsstöd när man bestämmer byggnadens design. Metoden utvecklades i steg, vilket presenterades i flera studier. I studierna användes fallstudier för att testa den utvecklade metoden och jämföra resultatet mot fältmätningar, vilka utformades för att utveckla, testa, verifiera och validera metoden.

Den första fallstudien använde den traditionella deterministiska metoden för att kvantifiera energiprestandan för småhus från 1960- och 1970-talet med fokus på att identifiera ekonomiskt lönsamma renoveringspaket till passivhusnivå samt vilken påverkan det skulle ge på energiprestanda för byggnadsbeståndet. Resultaten visade på potentialen och begränsningarna vid användning av den nuvarande simuleringsmetoden för att utvärdera olika designalternativ och kvantifiera energiprestanda och kostnader.

Detta följdes av en explorativ fas där alternativa metoder identifierades och jämfördes med det traditionella deterministiska tillvägagångssättet. Utvärderingen utfördes med hjälp av kvalitativa metoder för att urskilja när och i vilket syfte de alternativa probabilistiska metoderna kan vara fördelaktiga att tillämpa.

Baserat på resultatet av detta arbete började utvecklingen av metoden för probabilistisk riskanalys, vilket resulterade i flera studier med fokus på olika aspekter av metoden. Den första studien utvecklade och testade en experimentell version av metoden i en fallstudie som verifierade den resulterande prediktiva modellen för energiprestanda mot fältmätningar. Resultatet visade potentialen med

den utvecklade metoden och identifierade flera aspekter i behov av ytterligare utredning och utveckling. En aspekt handlade om den prediktiva modellens precision, vilket krävde ytterligare undersökning av datakvaliteten som användes som grund för modellen. En annan aspekt var hur man kvantifierar konsekvenserna av att inte uppnå designkriterierna och hur metoden kan utvecklas för att jämföra designalternativ och stödja beslutsprocessen med hjälp av en datadriven strategi. Dataupplösningen från fältmätningarna var dock grov, vilket minskade den analytiska potentialen genom att bara jämföra den aggregerade summan. Således var ett syfte med den följande fallstudien att öka dataupplösningen för att möjliggöra ytterligare analytiska jämförelser och med inriktning på datakvaliteten. Studien utvärderade hur olika nivåer av datakvalitet påverkar den förutsägbara modellens precision. Resultatet visade på vikten av datakvalitet och dess inverkan på den prediktiva modellen.

Den efterföljande studien utvärderade hur metoden kan utvecklas för att inkludera optimering av byggnadens design. Det implementerade optimeringssteget jämför designalternativ och hur intressentens synpunkter påverkar analysen och modellernas omfattning vid kvantifiering av risken. Studien utvärderade också hur de valda nivåerna på designkriterierna påverkar ett projekts risknivå. Utvärderingen illustrerar hur kvantifiering av risknivån kan förbättra beslutsprocessen, antingen när man beslutar om en byggnadsdesign eller vid valet av designkriteriet som ska användas i projektet. Målet är att denna studie ska tillgängliggöra användandet av deterministiska och probabilistiska metoder vid beslut gällande energiprestanda i byggsektorn.

De viktigaste resultaten från studierna var fördelarna med att implementera den probabilistiska metoden för att kvantifiera en byggnads framtida energianvändning och hur detta skulle kunna stödja beslutsfattarna under designprocessen. Metoden lägger till ytterligare dimensioner för datainsamling, utförande av simuleringar och analys, och visualisering och förmedling av resultaten. Istället för att tillhandahålla ett enda värde för en byggnads framtida energianvändning baserat på deterministiska metoder, så ger istället den probabilistiska metoden en fördelning av möjliga resultat baserat på empiriska data av osäkerheter för att kvantifiera sannolikheten för att uppnå kravställningen. Resultaten visade också betydelsen och effekten av datakvalitet och en strukturerad process för att samla in data.

Populärvetenskaplig sammanfattning

Avhandlingen beskriver en ny metod som använder probabilistiska energiberäkningar för att bedöma risken att en byggnad inte uppfyller ställda energikrav. Metoden beskriver hur den verkliga energianvändningen i byggnader bättre kan predikteras genom att osäkerheter gällande komponenters verkliga prestanda i den färdiga byggnaden och hur byggnaden verkligen används inkluderas i parametrar i beräkningen.

Den föreslagna metoden medför en utökad datamängd, som möjliggör att kvantifiera sannolikheten för att en viss prestanda uppnås, och därmed att konceptet risk kan tillämpas. Flera studier har genomförts där olika delar av problematiken har utretts och metodiken har kontinuerligt utvecklats baserat på resultaten. Även om ytterligare arbete krävs gällande sammanställande av data så har resultaten från studien visat potentialen med denna metod och hur den kan tillämpas i verkliga projekt. Förhoppningen är att detta ska leda till mer träffsäkra förutsägelser och därmed en framtida minskning i energianvändningen från byggnadsbeståndet.

Då byggnader står för ca 40 procent av den totala energianvändningen i EU, så finns det en stor potential med att begränsa energianvändningen i byggnader. En del i arbetet med att begränsa energianvändningen i byggnader är att noggrant kunna prediktera den i designfasen av projekt. Nuvarande metoder för att beräkna energianvändningen i byggnader har flera begränsningar i sin möjlighet att prediktera den verkliga energianvändningen, då beräkningen är beroende av parametrar som ej går att bestämma till ett exakt värde. Till exempel har boende olika rutiner och beteenden som leder till en stor variation när de är hemma eller vilken inomhustemperatur de föredrar. Men i beräkningar beter sig alla enhetligt. Skillnader som denna från vad som har antagits i de indata som används i beräkningen leder i sin tur till att när byggnadens verkliga prestanda mäts, så avviker den ofta från det beräknade värdet, då det beräknade värdet endast anges som ett specifikt värde, inte en fördelning av sannolika värden. Men, hade det i beräkningen tagits hänsyn till dessa skillnader i antal, tid och temperatur så hade resultatet bättre kunnat förutspå den verkliga energianvändningen. Detta angreppssätt, är vad denna studie försökt tillämpa.

Resultatet av studien är en strukturerad metodik för att genomföra energiberäkningar och riskanalys som tar hänsyn till osäkerheter baserat på sannolikhet, där tillämpningar för specifika fall har genomförts och resultaten visar på hur processen kan utföras, vilka möjligheter och begränsningar som finns samt problem som kan uppstå och hur de skulle kunna undvikas. Den data som sammanställts i projektet kan troligtvis appliceras även för andra fall av liknande karaktär för att underlätta implementeringen i framtida projekt.

Metoden utvecklades, beskrevs, testades och verifierades i flera fallstudier, först småhus och därefter flerbostadshus. I båda fallen utgjordes fallstudiens byggnader av en byggnadsdesign som byggts flera gånger under så liknande förutsättningar som möjligt. Detta val av byggnad gjordes för att kunna kvantifiera effekten av de osäkerheter som finns i byggnaden och jämföra mot resultaten från simuleringarna. Då samma byggnadsdesign har använts för de uppmätta byggnaderna så kan osäkerheter orsakade av en skillnad i utformning eller komponentval exkluderas från studien. Det som kvarstod var osäkerheter i verklig prestanda från de designval som gjort och hur brukarna skiljer sig åt. För dessa kategorier så identifierades parametrar för vilka osäkerheter i indata kvantifierades för att sedan simulera och bestämma den sammanlagda effekten på energiprestandan av dessa osäkerheter i indata.

List of Publications

This thesis's basis is the following peer-reviewed journal and conference papers, referred to in the text by their Roman numerals. The appended papers are at the end of the thesis:

Peer-reviewed journal publications:

I. Ekström, T., Bernardo, R. and Blomsterberg, Å.

Evaluation of cost-effective renovation packages to Passive House level for Swedish single-family houses from the sixties and seventies. *Energy and Buildings, Volume 161, the 15th of February 2018.*

II. Ekström, T., Burke, S., Hassanie, S., Wiktorsson, M., Harderup, L-E. and Arfvidsson, J.

Evaluating the impact of data quality on the accuracy of the predicted energy performance for a fixed building design using probabilistic energy performance simulations and uncertainty analysis. *Energy and Buildings, Volume 249, 2021.*

III. Ekström, T., Sundling, R., Burke, S., and Harderup, L-E.

Probabilistic risk analysis and building performance simulations – Building design optimisation and quantifying stakeholder consequences. *Energy and Buildings. (Submitted 2021-05-25, revised 2021-08-08)*

Peer-reviewed conference publications:

IV. Ekström, T. and Blomsterberg, Å.

Renovation of Swedish Single-family Houses to Passive House Standard – Analyses of Energy Savings Potential. *Energy Procedia, Elsevier Ltd, 2016. 96: pp. 134-145. Proceedings of the Sustainable Built Environment 16 Conference on Build Green and Renovate Deep, Tallinn, Estonia, 2016.*

V. Ekström, T., Davidsson, H., Bernardo, R. and Blomsterberg, Å.

Renovation of Swedish single-family houses to passive house standard - Sensitivity analysis. *Proceedings of 3rd Asia Conference of International*

Building Performance Simulation Association - ASim2016, Jeju (Cheju) island, Korea, 2016.

VI. Ekström, T., Bernardo, R., Davidsson, H. and Blomsterberg, Å.

Renovating Swedish single-family houses from the sixties and seventies to net-zero energy buildings. *Proceedings of Solar World Congress 2017, Abu Dhabi, UAE, 2017.*

VII. Ekström, T., Burke, S., Harderup, L-E. and Arfvidsson, J.

Possibilities with Probabilistic Methods for Dynamic Building Energy Simulations using Stochastic Input Data – Initial Analysis. *Proceedings of ASHRAE 2019 Thermal Performance of the Exterior Envelopes of Whole Buildings XIV International Conference, Clearwater Beach, FL, USA, 2019.*

VIII. Ekström, T., Burke, S., Harderup, L-E. and Arfvidsson, J.

Proposed Method for Risk Assessment using Building Performance Simulations and Probabilistic Methods. *E3S Web Conf., vol. 172, p. 25011, Jun. 2020. Proceedings of NSB 2020 Tallinn, 12th Nordic Symposium on Building Physics, Tallinn, Estonia, 2020.*

Licentiate dissertation:

Ekström, T.

Passive house renovation of Swedish single-family houses from the 1960s and 1970s - Evaluation of cost-effective renovation packages. *Printed by E-husets Tryckeri, Lund 2017.*

Author's Contribution to the Publications

Tomas Ekström is the first author of all the publications listed above. For all papers, all co-authors have contributed by reviewing and editing.

I. Ekström was the main author, responsible for the writing process, the modelling and simulations for the energy performance and cost calculation, and the data analysis. PhD Ricardo Bernardo performed the simulations for the production from the solar domestic hot water and photovoltaic systems and energy storage. Co-authors assisted with writing, analysis of data and discussion of results. The authors developed the idea for the paper together. PhD Åke Blomsterberg developed the research project.

II. Ekström was the main author, responsible for the writing process, provided input data, and analysed the data. MSc Samer Hassanie did the simulations.

PhD Magnus Wiktorsson helped with the input data and the data analysis. Co-authors assisted with writing, analysis of data and discussion of results. PhD Stephen Burke, PhD Lars-Erik Harderup and Prof. Jesper Arfvidsson developed the research project.

III. Ekström was the main author, responsible for the writing process, modelling and simulations for the energy performance and EPC cost calculation, and the data analysis. PhD Rikard Sundling provided input data, modelling and simulations for the LCC calculation. PhD Stephen Burke provided input data for the energy performance simulation. Co-authors assisted with writing, analysis of data and discussion of results. PhD Stephen Burke and PhD Lars-Erik Harderup developed the research project.

IV. Ekström was the main author, responsible for the writing process, provided input data, modelling, simulations, and data analysis. The authors developed the idea for the paper together. PhD Åke Blomsterberg developed the research project.

V. Ekström was the main author, responsible for the writing process, modelling, simulations, and data analysis. PhD Ricardo Bernardo and PhD Henrik Davidsson provided the input data. The authors developed the idea for the paper together. PhD Åke Blomsterberg developed the research project.

VI. Ekström was the main author, responsible for the writing process, modelling and simulations for the energy performance and cost calculation, and the data analysis. PhD Henrik Davidsson did the modelling and simulations for solar and energy storage. The authors developed the idea for the paper together. PhD Åke Blomsterberg developed the research project.

VII. Ekström was the main author, responsible for the writing process, compiled the information, and performed the analysis. Co-authors assisted with writing and discussion of results. The authors developed the idea for the paper together. PhD Stephen Burke, PhD Lars-Erik Harderup and Prof. Jesper Arfvidsson developed the research project.

VIII. Ekström was the main author, responsible for the writing process, modelling, simulations, and data analysis. PhD Stephen Burke provided input data. The authors developed the idea for the paper together. PhD Stephen Burke, PhD Lars-Erik Harderup and Prof. Jesper Arfvidsson developed the research project.

Abbreviations and Symbols

AHU	Air Handling Unit
BBR	Boverket's (The Swedish National Board of Housing, Building and Planning) building regulations – mandatory provisions and general recommendations.
BEN	Boverket's (The Swedish National Board of Housing, Building and Planning) mandatory provisions and general recommendations on the building regulations used to determine the building's energy use during normal use and a normal year.
BPS	Building Performance Simulations
CDF	Cumulative distribution function
DHW	Domestic Hot Water
DO	Design options
DHWCL	Domestic Hot Water Circulation Losses
EP	Energy performance
EPC	Energy Performance Contracting
FM	Field Measurements
G	Global
L	Local
LCC	Lifecycle cost
MOS	Margin of Safety
PDF	Probability density function
PRA	Probabilistic risk analysis
R&K	Room and Kitchen
S	Specific
S1	Scenario 1
S2	Scenario 2
SHGC	Solar Heat Gain Coefficient
T	Triangular
U	Uniform
VaR	Value at Risk

Contents

1 Introduction

As it so often does, this research originates from the discrepancy between the theoretical and real world. In this case, the energy performance of buildings and the theoretical ***predicted*** *- based on an abstracted model of a building using simulations - and* ***actual*** *- measured performance of the in-use building. Understanding why this discrepancy - often referred to as the energy performance gap - occurs and why the accurate prediction of the energy performance of buildings is important will be explained further in the section background. Nonetheless, this discrepancy can lead to misunderstandings and potential conflicts between the building contractor and building owner, creating financial and reputational risks for the involved stakeholders and a confidence gap regarding BPS.*

This research uses the concept of ***risk -*** *which consists of* ***probability*** *and* ***consequence -*** *to explain and predict the problem and bridge the knowledge gap between predicted and actual energy performance. There are several obstacles to implementing the risk approach for building energy performance simulations. These obstacles include deterministic methods, limited data availability, software capabilities, and computational power. With improved building performance simulation tools that include new functionality made available during the project, quantifying uncertainty and creating a predictive risk model is made possible. This research aims to develop and test a probabilistic risk analysis method during the design phase of building projects. The examples used were chosen to show the benefits and limitations of the proposed method to multiple stakeholders and presented in an accessible format for future use in the building sector.*

This thesis builds on the work conducted in a series of studies, reported in *Paper I-VIII*, [1]–[8], published or under review in international scholarly peer-reviewed journals and conferences. In addition, this thesis further develops the work previously published in a Licentiate thesis [9].

This chapter describes the background, aim and objectives, limitations, a summary of appended papers, and an outline of the thesis.

1.1 Background

As most countries in the world continue to reduce greenhouse gas emissions to mitigate climate change, as part of fulfilling the Paris Agreement [10], one area of focus with potential is buildings' energy efficiency. Buildings currently account for approximately 40 per cent of the total energy use in the European Union [11]. One solution for reducing the energy demand from buildings is by continually implementing more stringent building regulations, as stipulated by the Energy performance of buildings directive by the European Union (EPBD) [11]. The EPBD stated that by the end of 2020, the directive for near-zero energy buildings was to be implemented in European Union countries' national regulations, dictating newly constructed buildings [11]. The Swedish government has set an even more challenging goal, striving for a 50 per cent reduction in energy use by 2030 compared to 2005 in terms of supplied energy relative to the GDP [12].

Although regulation often focuses on reducing energy use in buildings through more stringent energy performance (EP) criteria, the primary function of a building is not to attain low energy use. Thus, the regulations often also include several other performance criteria for the indoor environment to provide healthy and safe buildings; the Swedish building code [13] includes, e.g. moisture safety, daylight requirements and the occupants' thermal comfort. However, this study is limited to the energy performance criteria for buildings designed to fulfil all building code criteria active during the design phase of each building project.

A method for ensuring that the as-built building fulfils the criteria is to use building performance simulation (BPS) to quantify the predicted performance during the design phase. The BPS uses a mathematical model of the building and systems to predict the output for a given input. The abstracted computer model of a building aims to replicate the critical building characteristics while the simulation replicates the real-world operation of the system over time. Depending on the desired output, there are many models, e.g. a neighbourhood of buildings, a whole building, or a building sub-system. The simulation predicts a potential future state of performance for a building under a specific set of conditions. The predicted future is only valid for the exact conditions used as input to the simulation. However, there are many possible futures in reality because of the variation in actual building usage or changes in future climate, and robust predictions need to consider this variety. The simulation outcomes then provide information to the decision-makers on the design option to choose. Combining the BPS with an optimisation process could result in a robust building and systems design solution that attains all design criteria at lower energy use.

Consequently, the importance of accurate and efficient BPS to predict the EP of a building design increases with more stringent regulation reducing the margin of error [14]. A quality assurance process to determine the appropriate level of resolution and complexity of the model, verifying and calibrating the model using a validated software and applying a correct design methodology should ensure a minimum level of accuracy of the predicted EP from BPS.

However, as observed in earlier studies [15]–[18], a performance gap exists between the predicted EP - using BPS and the traditional deterministic approach of assigning a single value per influencing parameter resulting in a single output value - compared to a building's actual EP. A study by the Swedish Energy Agency evaluating the actual EP of 31 buildings - single-family, multi-family, pre-school, and office buildings - designed to be low-energy buildings - found that 75 per cent of the buildings exceeded the design criteria for EP [19]. In a literature review study, de Wilde [20] proposed a framework for investigating the performance gap and described several potential causes throughout all phases – design, construction, and operations. The study identified the need to include uncertainties in predictions and that:

> "the performance gap can only be bridged by a broad, coordinated approach that combines model validation and verification, improved data collection for predictions, better forecasting, and change of industry practice." ([20])

According to Hong et al. [21], one of the ten most significant challenges to overcome in building simulations is the performance gap. A consequence of the performance gap is a confidence gap, e.g. the perception that the BPS outcomes are not trustworthy and not worth the effort.

The uncertainties that affect a buildings' EP originate from various causes and during all building phases, from early design to operation. Examples include; uncertain design choices; component properties; limited data; the operator's experience, knowledge and their interpretation of information; time-constraints; limitations in the simulation software; and the deviation between designed and real-world operation and occupant behaviour in the finished building [20], [22]. The uncertainties can be divided into different classes, depending on the source of the uncertainty. The classification of uncertainties presented by Rezaee et al. [23] clarifies and defines the different types of uncertainties, as shown in Table 1.

Table 1. Types of uncertainties
The classification of uncertainties in BPS according to Rezaee, R. et al. [14] shown in the table are applied in this study.

Type		Description
Numerical		Computational and numerical imperfections
Modelling		Modellers interpretation and abstraction of reality
Scenario		Boundary conditions, a scenario for building use
Design	Decided	Parameters with a specific design decision, physical uncertainty quantifying variability in material properties
	Undecided	Uncertainty in the evolution of the design

A common approach to compensate for the deterministic method's limitation in accounting for the real-world use of a building and reducing the performance gap is to use a normalisation process for both the predicted and actual performance. Thus, applying the process before comparing the predicted and actual EP against the design criteria to evaluate if a building attains the requirement during the design phase and as-built. The normalisation process aims to eliminate or reduce deviations in the building's actual use from the assumptions made when deciding on the input data that were the basis for the prediction. In Sweden, this process is described in BEN [24]. The process could include several normalisation steps depending on the identified causes that deviate from the standardised use defined in the regulation - represented in the input data - and that are out of the control of the building contractor, e.g. deviation in indoor temperature, household electricity intensity, and domestic hot water (DHW) usage. Hence, instead of improving the prediction, the real-world is assumed to be wrong because it did not fit the assumptions and is altered by morphing the measured data. An alternate approach would be to include the uncertainties of the real world in the prediction model instead.

One technique of identifying and quantifying the performance gap is to use uncertainty analysis, as Tian et al. [25] described, based on probabilistic methods to model and include the relevant uncertainties of the real world in the input data of the predictions. The process requires assigning stochastic parameters in the building model to perform multiple simulations to quantify the aggregated effect on the building's EP from the uncertain input variables. Each stochastic input parameter is assigned a probability distribution to sample the input data for each simulation. Finally, the uncertainty analysis uses the outcomes of the multiple simulations to create a predictive model to quantify the probability of attaining a design criterion. The development to include uncertainty quantification and stochastic parameters in BPS appears to have started in the 1990s and has developed since then [22], [26], [27].

An uncertainty analysis is different from a traditional sensitivity analysis. A sensitivity analysis often focuses on the *design undecided* uncertainty, using a uniform probability density function for all design options within the design space to identify which input parameter has the most significant effect on the output variable to prioritise between parameters and identify the significant parameters to improve. The subtle distinction between uncertainty and sensitivity analysis was described by Macdonald [22] as follows:

> "The aim of a sensitivity analysis is to discover the (typically few) input parameters to which the measured output of a model is sensitive, i.e. a change in a design parameter (say 1% less infiltration) would result in a relatively larger change in a performance metric (say 10% less heating energy required). A crucial aspect of a sensitivity analysis is that it is unnecessary to quantify the likely variation in the model's parameters. Conversely, in an uncertainty analysis the variation in the input parameters is critical to the analysis, as the aim is to discover the likely variation in the output due to the actual variations in the input. A side effect of this is that the model may be sensitive to a specific parameter but, if the parameter is well known, it is not a critical parameter in an uncertainty analysis."

A state of the art review regarding uncertainty analysis in building energy assessment is presented by Tian et al. [25], showcasing input data models, sampling methods and software available for uncertainty analysis. Tian et al. [25] identified the need for more research on optimisation under uncertainty, focusing on uncertain factors during the design phase. One method that applies this concept was developed and tested by Burke et al. [28], showcasing the potential to predict the variation in EP in a building during the operational phase comparing the predicted and actual EP.

Using uncertainty analysis for decision-making by quantifying the risk of a building design was proposed by Pettersen already in 1997 [27], and based on the same idea, Sun et al. [29] developed a framework for risk analysis using probabilistic simulations. However, they did not validate the prediction from their model against a population of buildings based on the same design. A study by Heo et al. [30] also developed a method using probabilistic approaches to quantify the risk of design options. However, the simulation models were simplified to enable the multiple simulations needed to quantify the uncertainty and a simplified consequence model with no uncertainties regarding the prices and costs of influential parameters were included in the cost analysis. In a later study, Heo et al. [31] included uncertainties in prices and costs; however, they still used a simplified consequence model and no examples showcasing the difference between stakeholders. Furthermore, the predicted uncertainty in EP was only compared to field measurements from a single building, thus not evaluating and validating the accuracy of the predicted risk. Similar limitations are evident in studies by Lee et al. [32], not including uncertainties in other influential factors in the cost analysis, and Sun et al. [29], which focused on evaluating the curve-fitting techniques to find a best-fit distribution to use for risk analysis.

In the studies, the number and types of uncertainties influencing the energy performance also differs. Another difference in approach is the aim and scope of the methods. In contrast, other methods are developed to focus on how to apply the approach for renovation projects, using the existing building to calibrate the uncertainty models; the focus in this study is to quantify generalised uncertainties influencing the energy performance during the design phase, regardless of if the method is applied to existing buildings or during the design phase.

This research project is based on the previous work by Burke et al. and continues by expanding the scope and developing a method that includes risk analysis. The concept of a risk analysis is to quantify the probability and consequence of an event occurring as a basis for quantifying a risk level. Thus, requiring the implementation of uncertainty quantification and a probabilistic approach in both the building performance simulations, enabling a predictive model to quantify the distribution of possible outcomes in EP of a building and the probability of fulfilling the EP criteria, and in the consequence model, to quantify the possible outcomes in consequence of not attaining the EP criteria.

The method and case studies described in this study explores an uncertainty analysis of a fixed building design and system by including the discrepancy between the declared property of a product, material, or behaviour quantified under specific conditions and the actual performance in real-world use.

Based on the identified performance gap and the arguments of de Wilde, this study set out to develop a method that includes uncertainties from the design, construction, and operational phases of a building, based on extensive data collection to improve and expand the input models, aiming to improve the accuracy of the predictions of the EP and consequently reducing the performance gap. The process included extensive model validation and verification to ensure the models' validity and evaluating the prediction's accuracy using case studies based on building designs built multiple times and data from field measurements.

1.2 Aim and Objectives

This study aimed to gain new knowledge regarding probabilistic methods applied to building performance simulations used to evaluate buildings' EP and understand how risk analysis could be implemented and used to improve the decision-making process for making informed decisions when deciding on design options for a building.

The hypothesis was that the energy performance gap could be quantified, accurately predicted, and consequently reduced by implementing a probabilistic approach for building performance simulations and a concept of risk.

The research questions from which this research project originates are as follows:

- What causes the performance gap?
- Could the performance gap be predicted using probabilistic energy calculation methods?
- What are the limitations with current methods for predicting the actual EP?
- What novel strategies, concepts or methods are available that could be implemented or improved upon to improve the accuracy of BPSs?
- What consequences are there for not attaining the energy performance criteria?

The objectives were:

I. Evaluate and test quantitative deterministic methods for EP and cost analysis to find a cost-effective EP level throughout the design space, highlighting advantages and disadvantages with current methods. (*Paper I, IV, V & VI*).

II. Investigate the advantages and disadvantages of deterministic and probabilistic methods, focusing on differences in handling sensitivity and uncertainty (*Paper VII*).

III. Develop and demonstrate a probabilistic risk analysis framework for BPS, using a probabilistic approach to quantify probability and consequence, allowing for evaluating building design options (*Paper III & VIII*).

IV. Investigate the impact of data quality on the accuracy of the predictive model (*Paper II*).

V. Explore how to integrate the analytical results from the PRA for BPS into the decision-making process during the design phase using visualisations (*Paper III*).

1.3 Limitations

The case studies performed within this research project were within a Swedish context, e.g., Swedish regulations, buildings, climate, and other input data. However, the method and conclusions are applicable elsewhere, though the input data needs to be revised based on local conditions.

The simulation of EP performed in this project was limited to the BPS software IDA-ICE, developed by Equa Simulation AB [33]. However, the general theoretical application of the method is tool-agnostic. For example, Burke et al. [28] tested their probabilistic method using a custom version of VIP Energy, developed by StruSoft [34].

The case buildings were all residential buildings, either single- or multi-family, limiting the work and current application of the method to these types of buildings.

The study does not include all uncertainties that impact the EP of buildings; thus, the researcher does not expect perfect accuracy when comparing the predicted and measured performance's variation and shape.

This project focused on the importance of data collection for uncertain parameters and how to identify, quantify, and include different types of uncertainties in the BPS of the developed method.

The *climate* and *numerical* types of uncertainty, described in section *1.1 Background*, were ignored when quantifying uncertainties. The studies presented in *Paper VIII and V* used a specific building design to eliminate the *design undecided* uncertainties. The study presented in *Paper III* used the specific design from *Paper VIII* and evaluated two specific design options. The quantified uncertainties were limited to those during the design and the first two years of building use.

The data from field measurements are limited to those collected based on the minimum level required by the Swedish building regulation, i.e. space heating, DHW and electricity for building services and measured data at an hourly level. Thus, more detailed data is not available and not for other categories, i.e. actual indoor temperature, and more detailed analysis of the performance gap or inaccuracies between predicted and actual EP is not possible based on the current dataset.

Including local energy generation and storage in the building design optimisation is currently ongoing work outside the scope of this study.

From an ethical perspective, all data collected during the project were aggregated data so that individuals and their actions were not identifiable.

1.4 Summary of Appended Scientific Publications

Paper I investigated the cost-effectiveness of different passive house renovation packages for Swedish single-family houses from the 1960s and 1970s using simulations based on the deterministic methods for quantifying EP and evaluating the cost-effectiveness using lifecycle cost analysis.

Paper II continued developing the probabilistic method from *Paper VIII* by evaluating the accuracy of the predicted EP and the dependency on data quality. Demonstrated using a case study and validated against field measurements from 28 buildings compiled during the study.

Paper III continued to develop the probabilistic risk analysis method for the EP of buildings from *Paper II and VIII* by developing the model for consequences and design optimisation to improve the decision-making process during the design phase. Demonstrated the method using a case study involving two design options and three stakeholder perspectives using two consequence models. In addition, validating the base case design options EP was performed in *Paper VIII*.

Paper IV identified building typologies representing the building stock of Swedish single-family houses built in the 1960s and 1970s, used as a base case for evaluating the energy savings potential for the building stock from implementing the evaluated passive house renovation packages.

Paper V evaluated the significance of design options for parameters using sensitivity analysis to quantify the variation in performance from various renovation options from *Paper IV*.

Paper VI evaluated the potential of achieving a net-zero energy building using the renovation packages from *Paper I* as a baseline and evaluating systems for local energy production and storage.

Paper VII described the deterministic and probabilistic methods, the advantages and disadvantages of the different approaches, and the difference in their scope and applicability.

Paper VIII developed the first version of the method for probabilistic risk analysis used as a basis in future studies. Demonstrated the method using a case study, with a specific design to quantify the distribution in EP and probability of failure and using one consequence model to quantify the risk of the design. The validation of the case buildings EP used field measurements from 26 identical buildings built using the design.

In addition to the above-described papers, part of the doctoral studies involved writing a Licentiate Thesis, published in 2017. The thesis was presented and defended to pass the Licentiate examination at Lund University.

The Licentiate was part of another project titled "*Passive house renovation of Swedish single-family houses from the 1960s and 1970s*". The project's focus was evaluating the energy savings potential of renovation packages using deterministic methods for BPS to predict the EP and sensitivity analyses to determine significant influencing parameters. During this work, the limitations of the traditional methods became evident and using the knowledge gained during the Licentiate project allowed for continued research regarding probabilistic methods for energy calculations.

1.5 Outline of the Thesis

Chapter 1 introduces BPS, different methodological options and their application, the energy performance gap and difficulties with predicting the energy use of buildings, the aim of the research project, and the research questions it aims to answer. Contents of subsequent chapters are as follows:

Chapter 2 – Theoretical background	gives a theoretical framework based on the literature review.
Chapter 3 – Research methodology	describes the overall research strategy applied in this project.
Chapter 4 – Results and discussion	presents the developed method and the results of all papers included in the thesis and relevant, unpublished investigations. Discusses the relevancy of the results to give context.
Chapter 5 – Conclusion and Future Work	presents the conclusions from the papers and an overview of how they impact each other. Proposes identified subjects of interest for future research.

2 Theoretical Background

This chapter defines the identified concepts needed as a basis for the continued research, including the theoretical background and concepts for risk, probability, consequence, unwanted events, financial consequences to stakeholders, building physics, energy performance, and data science.

2.1 Risk, Probability, and Consequence – What is it?

Before beginning the work to develop, implement, and test the concept of risk for EP in buildings, the first step was to define risk and the components included in the concept. The definition of risk, according to Kaplan and Garrick [35], is described as follows;

> "In analysing risk, we are attempting to envision how the future will turn out if we undertake a certain course of action (or inaction)." ([35], page 12)

Kaplan and Garrick [35] also described that when performing a risk analysis, the aim is to answer the following three questions:

1. What can happen? (i.e., what can go wrong?)
2. How likely is it that that will happen?
3. If it does happen, what are the consequences?

Furthermore, the focus of the risk analysis is on adverse outcomes. However, Kaplan and Garrick also argue that risk should always be considered within a decision theory context and present the risk of options relative to the cost and benefit of choosing either option.

More recent definitions of risk, such as in ISO 31000 [31], include positive and negative deviations from the expected outcome and emphasise risk management in the decision-making process. It is an iterative process that uses the output and new knowledge to learn and improve continually. ISO 31000 describes managing risks as principles (the what), framework (the how), and the process. Risk management should create and protect organisations' value by managing risks, making informed decisions, setting and achieving objectives and improving performance [36], [37]. The ISO 31000 guideline describes the eight risk management principles as;

> "**Integrated**: Risk management is an integral part of all organisational activities; **Structured and comprehensive**: A structured and comprehensive approach to risk management contributes to consistent and comparable results; **Customised**: The risk management framework and processes are adapted and proportionate to the organisation's external and internal conditions. They are also linked to the organisation's goals. **Inclusive**: Involving stakeholders in an appropriate and timely manner ensures that stakeholders' knowledge, views and opinions are considered. This provides improved knowledge and informed risk management. **Dynamic**: Risks can arise, change or disappear when an organisation's external and internal circumstances change. Risk management can anticipate, detect, determine and respond to these changes and events in an appropriate and timely manner. **Best available information**: The basis for risk management is based on historical and current data as well as on forecasts. Risk management explicitly takes into account any limitations and uncertainties of such information and projections; Information should be up-to-date, clear and accessible to relevant stakeholders. **Human and cultural factors**: Human behaviour and cultural factors have a significant impact on all aspects of risk management at all levels and at all stages; **Continuous improvements**: Risk management is constantly improved through learning and experience." ([36], page 3)

The principles described above guide this study's continued work to implement a risk analysis framework and process for EP criteria in buildings.

Thus, one definition of risk analysis is a systematic way of identifying hazardous events, determining the probability of the hazardous event occurring and the consequence when the hazardous event occurs. The risk is the combination of probability and consequence using a model, e.g.:

$$Risk(R) = probability(P) \cdot consequence(C)$$

The risk model has been defined in some variation and discussed previously by many [35], [38], [39]. Positive or negative outcomes impact various aspects in a practical application of risk assessment and analysis. Examples of aspects of risk are the financial, reputational and project risks. The applied field of risk analysis determines the specific factors that influence the outcome.

2.1.1 Risk Analysis – Applying the Concept of Risk

Most people have some concept of risk based on what they intuitively feel is a relatively more or less risky alternative. Thus, the concept of risk and risk assessment performed in everyday life are estimated based on experience and logical thinking, resulting in a subjective decision based on each individual's perception.

There are primarily two types of structured forms of risk analysis, qualitative and quantitative. The qualitative risk analysis uses a structured framework for performing the analysis while basing the analysis on the probability and consequence of human perception, while the quantitative focuses on applying mathematical models to quantify the risk.

An example of a structured qualitative risk analysis is using estimations based on perception and prior knowledge, often using a scale from low to high or numerical (1-3) to compare possible outcomes and indicate when and where to act, see Table 2 for an example of the concept.

Table 2. Example of a typical qualitative risk analysis matrix concept.
Shows an example of how to estimate the probability and consequence using a qualitative method for risk analysis. The action taken depends on the colour of the cell in which the estimation places a risk. For example, red, act; yellow, observe; green, acceptable.

Qualitative risk analysis matrice		Probability		
		Low	Medium	High
Consequence	High			
	Medium			
	Low			

An application of quantitative risk analyses is probabilistic risk analysis (PRA) or quantitative risk analysis. The PRA originates from the aerospace and nuclear sectors in the 1960s and 1970s [40]; today, it is widely used across many sectors. In addition, probabilistic EP simulations have been theorised and developed for some applications [29]. However, in the Swedish building sector, the primary application for PRA has been in the fire safety sector, to the design of a building's fire safety system [41], and in structural design.

2.1.1.1 Risk Tolerance and Profile

The concept of risk also introduces additional aspects that need consideration before performing the analysis, such as defining the stakeholders' risk tolerance and risk profile. However, these are subjective and individual aspects that require the specific stakeholder of a project to define. Thus, the process is to identify the risk profile, perform the risk analysis, and - depending on the outcome of the risk analysis - either accept the solution or adjust the solution and risk level and redo the risk analysis in an iterative process.

2.1.2 Probability – Theory and Definition

The branch of mathematics termed probability theory is a foundation for the work performed in this research project. The exact definitions and axioms are not described here but are available in the relevant literature on statistical theory and principles. However, described below are the main parts needed to understand the work performed in this research. According to Kaplan and Garrick [35], there has been disagreements about the meaning of probability for a long time. The argument is between the "objectivist" or "frequentist" school, who view probability based on the results of repetitive experiments, and the "subjectivists", who view the probability as an expression of an internal state – a state of knowledge or state of confidence. Probability is seen as a numerical measure of a state of knowledge, a degree of belief, a state of confidence. In comparison, frequency refers to the outcome of an experiment involving repeated trials and using the outcomes of the trials to calibrate the probability scale.

The probability space is a mathematical construct that models experiments where the outcomes occur randomly based on probability theory. The probability space consists of three parts:

1. The sample space, ξ, consisting of all possible outcomes.
2. A set of events, x, each consisting of a set of outcomes or observations.
3. Assignment of probabilities, as a function *P(x)*, to the events.

The assignment of probability is as follows. If repeating the experiment an infinite amount of times, each event's relative frequency of occurrence would coincide with the probabilities described by the function *P(x)*. Thus, the function describes the distribution for stochastic variables.

A method used to quantify the probability of failure, based on probability theory, is Bernoulli's Theorem [42] using Bernoulli trials, where the experiment is defined so as an event – a set of outcomes – has only two outcomes; these outcomes are either success or failure. Success *(p)* means that event occurred, fulfilling the specified conditions, and failure *(q)* means a complimentary – unwanted - event has occurred. The probability of these options can then be calculated and presented as equation 1:

$$1 = p + q \qquad (1)$$

The consequences of choosing an option are quantified using the area marked as a liability. Figure 1 shows an example of the Bernoulli trial and the area for consequence. Finally, deciding on the design option to use is evaluated using the quantified area of different design options.

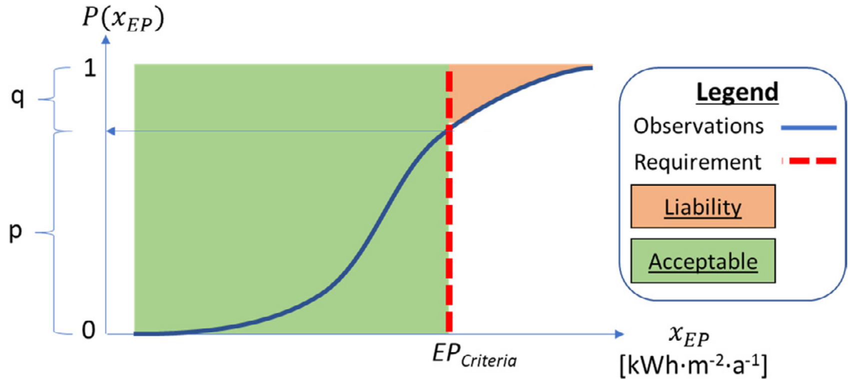


Figure 1. Illustration of a cumulative distribution function based on observations of EP for a building.
The vertical axis shows the Bernoulli trial's alternative outcomes - success (p) or failure (q) - based on the energy performance criteria for the EP on the horizontal axis used to quantify the probability of failure. Also illustrated is the area resulting in liability for not attaining the energy performance criteria used to quantify the consequences of failure.

2.1.3 Unwanted Events

An unwanted event occurs when not fulfilling a critical condition. When predicting the EP of a building design using simulations, the critical condition is the EP criteria agreed on in the contract between the stakeholders. The EP criteria could be based on the building code or a rating system with more stringent requirements. The systems define a numerical value for the EP criteria, commonly based on the energy use per heated floor area per annum (kWh·m^{-2}·a^{-1}) to compare different building designs and sizes (see the definition used in this study in section *2.2.1 Energy Performance*). There are various methods available to quantify the consequences of failure and ensure or at least reduce the risk of an unwanted event occurring. The sections below describe a definition and examples of stakeholders, systems used for quantifying the EP criteria, and consequence models used in the continued work.

2.1.3.1 Stakeholder Values – Goals, Preferences and Design Criteria

Applying the PRA method and defining the boundary conditions to use depends heavily on the project's stakeholders. Depending on the contract used or structure of the development team, all stakeholders have different values depending on the timespan they are involved in the building. Thus, different setups of stakeholders require a different set of stakeholder values to be defined, resulting in other outcomes from the risk analysis. Example of stakeholders:

- Building contractor
- Developer
- Planner
- Government or other governing levels
- Owner of the building

Each stakeholder requires a definition and quantification of an acceptable risk level using a design criterion. Quantifying the design criteria is relatively straightforward, often based on benchmarking systems or the building's actual performance; however, the risk level is subjective.

2.1.3.2 Design Criteria – Benchmarking Systems vs Actual Performance

Deciding on the input data used to create the predictive model depends on the scope of the study. Two typical scopes are benchmarking or actual performance. The stakeholders decide the scope based on the stakeholder values. Thus, the scope sets the project's design criteria and boundary conditions and determines the methods used to predict the performance criteria.

The design criteria for a building's EP in a project often use a benchmarking system that defines and quantifies a metric used to evaluate EP. The metric for EP is compared to the predicted EP during the design phase and verifies the building design's actual EP when built. Instead, other systems use the actual measured performance as a requirement to verify the building design's EP. The benchmarking systems commonly provide standardised input data for the building model when predicting EP. However, as the performance gap indicates, this input data does not fit the buildings' real-world use.

The Swedish building regulation requires that buildings fulfil the requirements on EP and that the energy use be simulated during the design phase using a dynamic BPS tool with deterministic methods [13]. Predicting a building design's code compliance requires calculating the EP using a simulation to quantify the energy use for space heating (SH), DHW and electricity used by building services (EBS). The regulation also requires that the completed building's energy use be measured uninterrupted over 12 months within the first two years of operation. The energy use is normalised and compared to the regulatory requirement to determine if the building fulfils the regulation. The types and sources of uncertainties quantified and used in this study are limited to those occurring during the design phase until the two first years of building use.

In addition to the regulations stipulated in the building code, the developer often includes more stringent requirements on the building's EP. The more stringent requirements often use already defined systems such as building rating systems and assessment methods, e.g. LEED (Leadership in Energy and Environmental Design) [43] and BREEAM (Building Research Establishment Environmental Assessment Method) [44] or energy performance contracting (EPC).

Using the benchmarking approach requires a normalisation process for the measured EP to eliminate deviation in the building's actual use from the prediction's assumptions before comparing.

2.1.3.3 *Models for Quantifying the Cost of Unwanted Events*

Described below are two examples of methods for quantifying the costs of an unwanted event as described in *Paper II*. The two methods showcase available options; however, deciding on the most suitable option will be case-specific and adapted to each project.

Energy Performance Contracting - From a building contractor's perspective, the EPC model quantifies the consequence of not fulfilling the contracted EP design criteria. The EPC concept is where the contractor pays a pre-determined penalty to the client/building owner if not meeting the design criteria. The penalty could include a set amount per measured kWh above the design criteria, a fixed value, or modifications to the building, so the energy use is reduced and fulfils the design criteria. The example used for the EPC is a standardised contract used in Sweden, *Sveby avtal 12* [45]. The Swedish building industry regarding developed *Sveby avtal 12* increase the incentives to fulfil the EP design criteria for buildings. The contract defines a fine (C_F), in SEK per kilowatt-hour, for the actual EP that exceeds the contracted level for EP (EP_R). The options available for the building contractor are either correcting the building through measures to improve the EP to the contracted level or paying a fine until the end of the warranty period (10 years); see equation 2.

$$Q_S = \sum_{i=1}^{10} \left(C_F \cdot (EP - EP_R) \right) \tag{2}$$

Lifecycle Cost - The lifecycle cost (LCC) analysis is another quantitative method used to assess design options, improve the decision-support, guide decision-makers to high-quality decisions, and optimise building design based on stakeholder values. Using the method requires a broad approach to avoid sub-optimising the building design. This method considers all costs that can occur during the lifecycle by calculating the net present value of these costs. According to Lind [46], a method that considers a whole lifecycle is an important tool for assessing long-lived investments such as renovation projects. The equation for calculating the lifecycle cost (e.g. [47]), see equation 3. The equation includes the calculation period in years (N), the initial acquisition cost (A_i), the operational costs in year n (C_n), the real interest rate (i), and the real price change in year n (q_n). It is important to note that the costs considered are case-specific and several different costs are likely to apply. Another aspect to take into consideration is the price change of the costs over time. The price changes will be considered here for more realistic prognoses.

$$LCC = -A_i + \sum_{n=1}^{N} \left(\frac{C_n \cdot (1+q_n)}{(1+i)^n} \right) \tag{3}$$

This consequence model introduces several uncertainties regarding the quantifications of costs that are evaluated later.

2.2 Energy Performance – Definition and Uncertainty

There are two alternative approaches to defining requirements on a building design during the design process, the prescriptive and performance approach, as discussed in [48]. The prescriptive approach details the performance of components in a building, e.g. earlier versions of the Swedish Passive house standard [49] included the requirement that windows must have a maximum thermal transmittance of 0.9 $W \cdot m^{-2} \cdot K^{-1}$. The performance approach focuses on what a building has to do, the functions to provide and fulfil, and how well it performs by assessing the building performance objectively to identify an optimised design that fulfils all the requirements, which is the approach of the Swedish building code [13]. The optional compliance paths are also available in the International Energy Conservation Code [50]. This study follows the performance approach; thus, requiring a definition of the objective for energy performance.

The definition of EP in the section below describes the types of energy use included. The process for calculating EP could be applied both to simulated and measured energy use for a building. The simulated energy use quantifies the predicted EP, and the measured energy use quantifies the actual EP.

The quantified energy use for both simulated and measured includes multiple factors that influence the energy use. Identifying factors and analysis of influence is required to understand the quantified levels of energy use and differences between them. For the simulations, these uncertainties primarily regard the input data and the accuracy of the assumptions. For the measured data, the uncertainties for the as-built building relates to if built according to design, occupant behaviour, and measurement errors in the field measurements. The section below describes an overview of influencing factors and uncertainties with examples.

2.2.1 Energy Performance Criteria

As described in *Paper II*, EP was defined based on the Energy performance of buildings directive [11] as delivered energy used for space heating, DHW, and electricity for building services. This study calculates EP according to the definition in the Swedish building regulation [13]. The regulations define the building's EP ($kWh \cdot m^{-2} \cdot a^{-1}$) as delivered energy used per year ($kWh \cdot a^{-1}$) in the building for space heating (E_{SH}), DHW (E_{DHW}), and electricity for building services (E_{EBS}) divided by the heated floor area (A_{temp}) (m^2) and calculated according to equation 4. Active cooling is uncommon in Swedish residential buildings and was not available in the case study buildings. Thus, cooling is excluded from the method described.

$$EP_i = \frac{E_{SH,i} + E_{DHW,i} + E_{EBS,i}}{A_{temp}} \tag{4}$$

2.2.2 Influencing Factors and Uncertainties

Six main factors influencing the EP of buildings according to Annex 53 [51] are; 1. climate, 2. building envelope characteristics, 3. building services and energy systems characteristics, 4. building operation and maintenance, 5. occupant activities and behaviour, and 6. indoor environmental quality. Within each influencing factor, there are various *sources of uncertainty* affecting the actual performance of a factor.

Below are examples of sources of uncertainty found in the literature based on influencing factors and the types of uncertainties. Although, this excludes some categories mentioned in section *1.3 Limitations*. One is the climate-related uncertainties. Another excluded category was the uncertainties associated with indoor environmental quality, such as operative temperature. However, factors such as the indoor air temperature, air flow of the ventilation, and kitchen fan depend on or impact the indoor environment.

When quantifying uncertainty, it is vital to consider the difference between the declared property of a product or material, quantified under specific conditions, and the actual performance in real-world use.

The first category of sources of uncertainties is regarding the **building envelope characteristics**. The building envelope includes various elements consisting of several dissimilar materials and layers that affect the elements' thermal transmittance. These variations in the individual elements influence the overall thermal performance of the building envelope. In studies investigating and optimising a building's design space, the commonly included uncertainty is the *design undecided* uncertainty. The *design undecided* uncertainty often includes alternative building envelope designs, e.g., the external wall's specific design. However, even if the component's design is known, eliminating the *design undecided* uncertainty, the *design decided* uncertainty remains. The study by Burke et al. [28] shows an example of quantifying the *design decided* uncertainty for mineral wool's material property and a window element's thermal transmittance. Using data from laboratory tests - commissioned by the Swedish National Board of Housing, Building and Planning - observations show a discrepancy between the real-world versus the declared performance of mineral wool batts [52] and thermal transmittance of windows [53]. The discrepancy highlights the relative deviation and stochasticity of parameters commonly assumed to be deterministic. Another source of uncertainty is the ***airtightness of the building envelope.*** Even when constructed according to specification, the performance depends on the workmanship during the construction process. When measured, significant deviations can be found regarding the airtightness at both a local level, for example, separate apartments of a building and a whole building (global) level – which can be seen in Wisth [54]. There are also differences at a building stock level, as Fahlén et al. [55] show when evaluating a neighbourhood of 26 identical buildings with an on-site factory manufacturing the building envelopes. Another often ignored uncertainty is the ***built-in moisture losses.*** Two common energy losses can occur due to moisture in building materials. The first is when moisture from the building materials, for example, concrete, evaporates into the indoor air. This process requires energy [56], [57]. The second example, not relevant to the case study and thus excluded from this study, is trapping moisture between two impervious layers, and the moisture evaporates and condenses between the warm and cold sides. One of the earliest energy calculation programs to incorporate this was WUFI Plus, 2003 [58].

The second category of sources of uncertainties is regarding the **building services and energy systems characteristics**. This category includes the **building operation and maintenance** sources for the heating, ventilation, and air conditioning systems, consisting of several systems and products used to ensure the building performance, i.e. indoor climate and EP. This system has several sources of uncertainty. An example of this is the air handling unit (AHU) used for mechanical ventilation in this study's case building, a central unit servicing the whole building with a constant air volume system and a rotating heat exchanger. The forced kitchen hood ventilation function is connected to the AHU, used when cooking food to increase the airflow and bypass the heat exchanger to avoid contamination. This system introduces a *scenario* uncertainty on how often and for how long each occupant uses this feature. The **supply and return airflows** are designed and built to specific flows. However, the allowed variations in the measurement and calibration standards [59] introduces *design decided* uncertainties for the actual airflow. Other examples of uncertainties affecting the AHU's performance are the **heat exchanger's efficiency**, **supply and exhaust fan efficiencies**, and the **temperature setpoint controller** for the supply air. The specific fan power depends on the total resistance in the ventilation system, which is dependent on, e.g. the length, number and angle of bends, and smoothness of the ducts and the filter's resistance.

The third category of sources of uncertainties is regarding the **occupant activities and behaviour**. Research has shown that the occupants' activities and behaviour significantly impact a buildings' energy use, and the influencing factors are differences in the occupant's culture, lifestyle, occupation, and preferences [60]. A driver for these differences is the occupants desire to achieve comfort within their environment [61]. Dividing the occupants' impact on the EP of a building into factors introduces the following parameters. The **number of occupants** in a space, the age and size of the occupants, when the occupants are present in the space, how they move and act in that space, the intensity and type of activity, the heat gain from the occupant, the **household electricity**, the **DHW** use, the preferred **indoor temperature setpoint**, the **opening and closing of windows** or usage of blinds, and usage of the **kitchen hood fan**. In a building stock, all these parameters are stochastic and thus challenging to model and predict.

Lastly, the design phase also introduces other sources of uncertainty. An overarching and significant factor is the ***heated floor area,*** A_{temp} (defined by BBR

[13] as the floor area in m² heated to above 10°C), used in the EP normalisation process. The floor area is commonly quantified either by measurements from drawings or as an output from a computer model of a building. The output from both methods are dependent on the interpretation and accuracy of the person performing the measurement. The uncertainty regarding the actual ***heated floor area*** was one parameter that emerged during a BPS competition held in Sweden [62]. During the competition to evaluate which contestant could best predict the actual EP, an unexpected variation in the evaluated building's heated floor area emerged when evaluating the answers [63]. Pasichnyi et al. [64] quantified a significant deviation – ranging from 0 to 120 per cent – in a study where the declared heated floor area for the same objects (15 068 metering points) from two data sources – the database for EP certificate and the district heating suppliers – were compared for inconsistencies. These examples highlight the impact of the modellers' interpretation of the problem and introduce a *modelling* uncertainty source. The deviation significantly impacts the quantification of a building's EP.

Thermal bridges are another example of *modelling* uncertainty. For example, using a simplified model to include the thermal bridges in BPS, quantified using a standardised value – in per cent – added to the building envelope's overall heat transmission coefficient. Studies by Berggren et al. [33] have compared the simplified method of including a thermal bridge to calculated values and show how imprecise the simplified method is. While using a standard value for thermal bridges is a flawed method, it is advantageous in early phases when details of the building envelope are undecided (introducing the *design undecided* uncertainty). The more precise method of modelling and simulating thermal bridges' geometry requires that the design (or design options) and materials are known while introducing a *modelling* uncertainty regarding how the modeller interprets and approaches the problem, as shown in Berggren et al. [65].

These parameters and more were quantified and modelled in this project.

2.3 Data – Definitions, Concepts, and Methods

According to Kitchin [39], data are the raw material produced by abstracting the world into categories, measures and other representational forms, i.e. numbers and characters, establishing the building blocks used when creating information and knowledge. Ways of classifying data are by their form (quantitative, qualitative), structure (structured, semi-structured, unstructured), origin (captured, derived, exhaust, transient), generation (directed, automated, volunteered), source (primary, secondary, tertiary), type (indexical, attribute, metadata), access (closed, shared, open) or ownership (private, public). However, data is not useful in itself; it is first when meaning or value is extracted from data that they are useful. Extracting value from data requires the use of data analytics and data analysis techniques.

2.3.1 Data Analytics

A definition of data analytics is analysing raw data to draw out meaningful insights used to determine the best course of action. However, there is a range of different methods, techniques, and data analysis types, depending on the data and insights to uncover. Furthermore, there are both quantitative data and qualitative data, requiring different approaches to analyse. An overview of the four types of data analytics methods and what the techniques try to answers [66]:

- **Descriptive analysis** – describes "what happened" through summarising past data.
- **Diagnostic analysis** – describes "why it happened" using descriptive analysis identifying pattering in the data through detailed information to gain insights to identify the causes of those outcomes.
- **Predictive analysis** – attempts to answer, "what is likely to happen", utilising previous data to make logical predictions about future outcomes of events—relying on statistical modelling for forecasting.
- **Prescriptive analysis** – combines the insights from all previous analyses to determine the course of action to take in a current problem or decision.

Moving down the list increases both the complexity and added value contribution from the analysis.

2.3.2 Data Sampling Method and Uncertainty Propagation

The probabilistic method requires a large set of outcomes to enable statistical analyses. A process of multiple simulations - using randomised sampled input data for the stochastic parameters (X) and constant values for the deterministic parameters for each version of the simulations (i) - was used to produce the dataset. A sampling method that can handle various input data types - with different units and variations - was needed to use the probability distributions for generating input data for simulations. This study chose the Monte Carlo method because of the focus on quantifying the building design's aggregated uncertainty. The method used to maintain the uncertainty propagation throughout the process was the random sampling method. Using the random sampling Monte-Carlo technique, a numerical value for each parameter, and each simulation, was sampled from the stochastic parameter's cumulative distribution function (CDF) to create a dataset, represented by the n-by-m sampling matrix $\boldsymbol{X}$ (see equation 5).

$$\bar{X} = [X_1, X_2, \dots, X_m] = \begin{bmatrix} x_{1,1} & \cdots & x_{1,m} \\ \vdots & \ddots & \vdots \\ x_{N,1} & \cdots & x_{N,m} \end{bmatrix} \tag{5}$$

The last step was to use the sampled dataset to evaluate the building model N times, once for each row of the sample (5), creating an input-output map within the input space defined by the uncertainties and for each dataset and compile the obtained output, N possible results, see equation 6:

$$\bar{Y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{bmatrix} = \begin{bmatrix} f(x_{1,1}, x_{1,2}, \dots, x_{1,m}) \\ f(x_{2,1}, x_{2,2}, \dots, x_{2,m}) \\ \vdots \\ f(x_{N,1}, x_{N,2}, \dots, x_{N,m}) \end{bmatrix} \tag{6}$$

3 Research Methodology

This chapter describes the epistemological framework and research process, followed by empirical research, data processing, research strategy, and validation.

3.1 Epistemological Framework

This research follows the positivist research paradigm, as described in [67]. This paradigm is based on objectivist ontology, where social reality exists irrespective of the observer and is assumed to be patterned, orderly and stable. Thus, enabling the discovery of regularities and formulation of explanations and causal laws underpinned by epistemological realism. The logic of inquiry used in the positivist paradigm is the hypothetic-deductive, beginning with a literature review of a specific problem to assess previous research, used to identify and formulate knowledge gaps. Developing an empirically testable hypothesis uses deductive logic derived from theoretical propositions found in the literature. Testing the hypothesis requires quantitative methods, experiments and case studies, and statistical modelling techniques to discover and answer relationships between well-defined concepts expressed as measurable variables to explain, predict, and control phenomena. The research should be conducted value-free and objectively, based on facts.

3.2 Research Process

In this research project, all the individual studies performed to answer specific research questions follow the positivist research paradigm, from identifying the knowledge gap and research questions to deciding the methods used to test and predict the phenomena researched. However, qualitative methods were also applied when describing and evaluating the advantages and disadvantages of deterministic and probabilistic quantitative methods.

The primary research strategy used to gain more profound knowledge and understanding of the research questions was the case study, further explained in section *3.5 Research Strategy*. As with most quantitative research, compiling, structuring, verifying, and validating the data was a significant part of the work.

Section *3.4 Data* describes the process for the data verification and validation metrics. The data collection involved using various sources and data triangulation to enhance the credibility of the research's data, models, and results.

3.2.1 Developing a Method for Probabilistic Risk Analysis

Developing a method for using a probabilistic approach for EP simulations and risk analysis started with an overview of the processes required to quantify the EP, define what risk is, how to perform a risk analysis, and quantify probability. The study began with an exploratory study to gain familiarity with the subject, identify the state-of-art and define the knowledge gap and continued work. For this, the inclusion and combination of theory, concepts, and methods from various disciplines were required to explain and predict the phenomena, as shown in Figure 2.

Figure 2. Overview of theory and concepts relevant to the study
Illustration of the disciplines of interest for the hypothesis of this study described in section 2 Theoretical background.

Before continuing the development, the next step was to use decomposition of these overall concepts into research questions. An overview of the identified problems and questions is presented in the list below, followed by a knowledge discovery phase performed through a literature search and review process for the identified subjects.

Risk, probability, and consequence

- What are the definition and cause?
- How to quantify
- Risk assessment and analysis

Data and data science

- Methods for compiling, handling, and analysing data
- Data quality - validation and verification of data
- Biases and confounding factors

Statistical analysis and sampling methods

- Monte Carlo
- Regression analysis

Building performance simulation

- Performance gap
- How the accuracy of the output depends on the level of detail/granularity

Uncertainty quantification

- What is the definition and cause of uncertainties?
- How to identify and quantify uncertainties
- Could the uncertainty be reduced?

The building process and decision making

- How to enable a data-driven decision process?
- How to visualise data and results to enable correct decisions?
- Stakeholders - Values and preferences
- Phases of the building process
- Misunderstandings, misconceptions, viewpoints and behaviours

3.2.2 Current and Previous Methodological Limitations

The basis for this method has been used in other fields, as described earlier. However, there have been, and currently are, some limitations in the BPSs used to quantify the EP of buildings that have previously made it infeasible to perform this type of analysis. Some of these aspects are the following:

- Available data
- Computational power
- Limitations in simulation software
- Knowledge gaps
- Methodology

A significant limitation is the data available for the stochastic parameters used as input data in the simulations. This limitation is possible to work around by inference. Nevertheless, it is still, and likely will always be, a limitation, even after the compilation performed in this project and the results.

Limitations in simulation software and computational power have been, up until now, significant limitations to implementing this method. An often-used solution to this limitation has been to develop simulation software with simplified models that reduces the computational power required by sacrificing the accuracy of the results.

In this project, two software suppliers for BPS were involved and developed their respective software to implement the required calculations. However, the studies presented in this thesis only used the results from one software supplier.

Simultaneously, high-performance or cloud computing has evolved in recent years, potentially making time-consuming simulations such as these a problem of the past.

The knowledge gaps identified are regarding specific parts of the method and how it is possible to apply it regarding buildings' EP.

3.2.3 The Steps of the Evaluations and Analyses

Developing the probabilistic approach began with answering how and when to use the method, what to use it for, and who should use it, as illustrated by Figure 3. The work continued by dividing the questions into steps, with an overview of the steps shown in Figure 4. Below is a more detailed description of the steps.

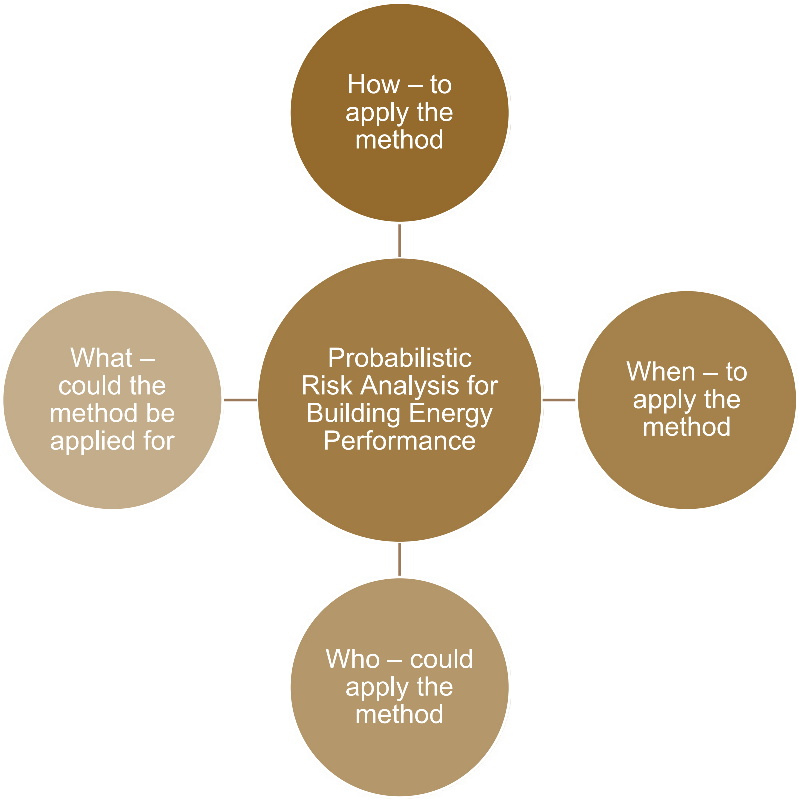


Figure 3. Overview of the question used to test the method.
Each question resulted in different studies performed in the project.

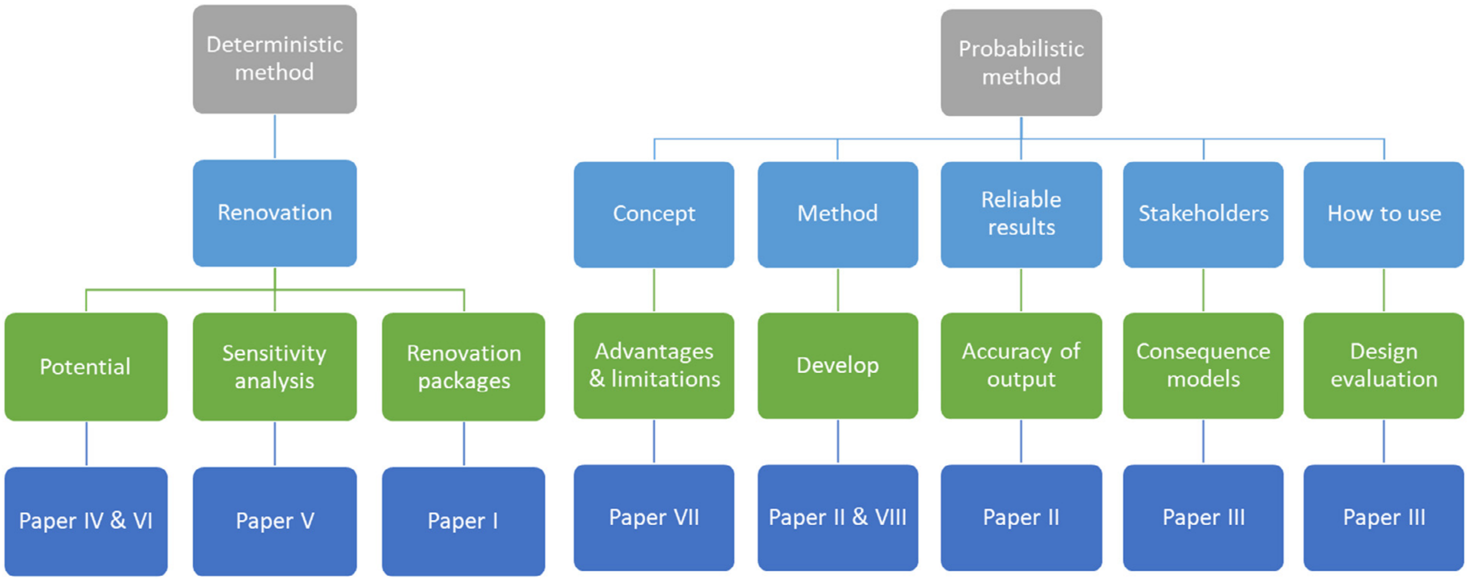


Figure 4. An overview of the process and papers.
Presents the applied methods, the research question in focus, and included in which paper.

In the first phase (*Paper I, IV, V, and VI*), traditional deterministic methods for quantifying the EP and cost evaluations were applied and tested to demonstrate how the design space exploration could affect the response in aggregated EP and costs and how to identify cost-effective renovation packages of various solutions. The process contained case identification and selection steps, focusing on mirroring the building stock's variance from the specified timeframe. Potential design options were selected from the base case of the identified case buildings to illustrate and quantify the effect of implementing commonly used design options for the building envelope and system components.

Developing and improving the PRA method uses three steps iteratively: development, testing, and validation. The first step was to quantify the total potential in response to the design space (*Paper IV*). The second step was to quantify the effect on EP by various parameters by applying a traditional sensitivity analysis (*Paper V*). The sensitivity analysis uses different design options to identify the most significant input parameters affecting the response in EP for the case study buildings. The aim was to identify and evaluate the cost-effectiveness of three renovation packages, each attaining a different level of energy performance. The process of deciding the combinations of design options uses the knowledge and data gained in previous studies. The EP and cost-effectiveness were quantified and evaluated, presenting a method for evaluating cost-effective renovation packages for different building typologies and different base cases (*Paper I*). In addition to reducing the energy demand, the focus of the subsequent study (*Paper VI*) was on implementing local production of heat and electricity to evaluate the potential of attaining a net-zero energy building using one, or a combination, of solar heating, photovoltaic cells and battery storage.

The first phase showcased the limitation with current deterministic methods for BPS because of the extensive time required to create, model, and simulate the design space's vast variation, while only resulting in one specific value for each alternative, thus not giving any indication of the performance gap. Since the results from the simulations should be similarly inaccurate in predicting the actual EP of a building, the absolute error should decrease by using relative values. Hence, the results are valid when comparing options - using the difference in results as relative values to quantify the effect on a design change's response. Novel methods are needed to increase the predictive model's accuracy by incorporating real-world stochasticity into the predictive model.

While the first phase focused on evaluating the design space using sensitivity analysis and manipulating the input data using design options in a controlled setting to identify parameters with a significant effect on the response, the second phase neutralised the design space by only using one building design per case study. The focus changed to uncontrolled factors, using the decomposition method to identify and divide the building into components and factors with uncertain performance. Based on the identified factors, a data collection process began obtaining data and models from various data sources based on observations of the input variables' variance in performance.

The evaluation process began by using qualitative methods to evaluate the options, define the methods, and compare them to each other regarding their potential of predicting the EP of building designs and other essential aspects for BPSs (*Paper VII*). The study evaluated the advantages and disadvantages of the methods. The evaluated factors included how to predict the performance gap, the complexity of models and input data, the computational power needed, and time for modelling and analysis.

After determining the advantages and potential of using probabilistic methods, the focus shifted to implementing BPS and risk analysis. The process continued by performing a literature review to identify and evaluate current methods and limitations, how previous studies have applied the methods, compile data sources, and collect data.

A probabilistic method for risk analysis of building designs was developed based on the gathered knowledge and information. The method was tested using case studies, applied to a single-family house (*Paper III & VIII*) and a multi-family house (*Paper II*), and validated against measured EP in both cases. The reason behind using a multi-family building was to expand the method to a more complex building model, implementing additional uncertain parameters and introducing a temporal variability for parameters. The numerical and modelling errors are identified, evaluated, and eliminated using the same model and input data and performing the simulation in two independent simulation software. Although currently unpublished, the models and results were verified using the results from the two software before continuing with the specific evaluations of the studies in the papers.

The next step was to evaluate the accuracy of the predictive model. Evaluating the accuracy's dependency on data quality uses two sets of input data obtained from various data sources and how the decision-maker's choice of different project design criteria impacted a building design's risk level (*Paper II*).

The last step was to use implement consequence models and enable optimisation, using two design options to showcase how the developed method could optimise the building design and multiple stakeholders and two consequence models (*Paper III*).

3.3 Building Physics and Performance Simulations

The research performed was within the field of building physics and based on quantitative methods for calculating and predicting the annual energy use of buildings using BPS based on gathered empirical data for the underlying model parameters. The studies of this project use simulations as experiments to test and evaluate the research questions. Thus, it is part of the applied sciences since the aim is to solve a specific problem. An overview of the concepts and approaches used are described here, however for a complete overview of the field of BPS and analysis, see relevant available literature, e.g. Building performance simulation for design and operation, by Hanssen and Lamberts [68] and Building Performance Analysis, by de Wilde [69].

As defined earlier in section 2.2.1 Energy Performance Criteria, quantifying the EP of a building requires the annual energy use of the building for space heating, DHW, and electricity for building service. The energy use for these categories was quantified using computer simulations performed using validated dynamic BPS software to simulate the operation of the building.

A building model is required to perform the simulations. The computer model of the building represents an abstracted and simplified version of the real-world building design, created using a graphical user interface to model the building geometry and systems. The software creates a mathematical model to calculate the annual energy use of the modelled building using dynamic boundary conditions. The simulation requires quantifying input data for the critical underlying model parameters and other factors such as the simulation period and time-step of the simulation.

Predicting the EP using BPS and an abstracted computer model of a building to represent the building characteristics and real-world operation requires balancing factors such as aim, design criteria, time- and cost constraints. One aspect of the balancing act is the granularity for the data resolution for the input models and the computer model of the building, the spatial and temporal resolution, and the impact on the robustness of the output. Changing the resolution for one of the factors impacts the others.

The current paradigm within regulations when using BPS is a deterministic approach to quantify EP. The following chapters include a description of the framework used to create the probabilistic risk analysis method. The steps include identifying, describing, developing, testing, and validating a probabilistic approach for quantifying the EP and how the probabilistic approach enables an improved risk analysis for support when deciding on options for the building design.

A quality assurance process was applied to the models and simulations to ensure the accuracy of the results. The process includes several steps. These include analysing the building and input data to determine the appropriate level of resolution and complexity for the computer model, verifying and calibrating the model using a validated software and a deterministic approach and standardised input data, verifying and calibrating the model using two independent software for the probabilistic approach, and validating the outcomes against field measurements from the modelled objects.

The BPS and quality assurance process include creating, testing, verifying, calibrating, normalising and validating models and methods, and in which phase to perform them is described below. The scope of the study decides the relevant parts. For example, specific input data is often provided for a benchmarking system, eliminating the calibration of input models.

Design phase:

1. Create the model for the building geometry and systems with relevant input data.
2. Verification – Simulating the model and evaluating the input data and outcomes are within expected ranges.
3. Optimisation – Changing the building design or systems to attain the desired performance.

Operational phase:

4. Normalisation – The predicted and measured performance is normalised to enable a comparison.
5. Validation – Comparing the verified and calibrated model outcomes against empiric data from the as-built building.
6. Calibration – Input models: Detailed data from the field measurements enables calibration of the input models based on the differences between expected and actual usage and performance.

The case studies performed in this study used some or all of these steps. The first phase of this project only performed steps 1 and 2; thus, the outcomes of the studies were not validated, only identifying the potential of the proposed method and solutions. The second phase varied in the used steps. The case studies applied to the single-family house only used steps 1-5 because of limitations in the details in the data. The case study applied to the multi-family house used all steps. However, if more detailed data were available, the last step could have delved even deeper into the causes for the deviations.

3.3.1 Simulations and Software

This study used different software for the data collection, processing, sampling, energy simulations, and post-processing. The software used is presented with a short description in Table 3.

The objectives of the research project required a dynamic multi-zone building performance simulation software for the simulations. The commercial dynamic energy simulation software IDA-ICE, developed by EQUA [33], was used.

The project used several versions of the software for the simulations. The first phase used the – at the time – commercial version of the software (4.7). During phase two, the project collaborated with the developer to use both the beta version of 5.0 and a customised version.

The code of the software was modified to include the probabilistic method using stochastic input data. The simulations used whole-building models. The floor area referenced in this study is the heated floor area (A_{temp}) if not otherwise stated. The simulation period of the performed BPS simulations was one year and with a time step of one hour.

Table 3. The software used in the study.
The table presents a description of the software, the software supplier, and its use in the study.

Simulation software	Description
IDA ICE	IDA Indoor Climate and Energy (IDA ICE) by developer EQUA [33] is a validated dynamic BPS software. The EP was quantified using the software to simulate the energy use of the case buildings. The first part of the project used version 4.8. The second part of the project used IDA ICE 5.0 beta for simulating the EP in the case studies.
HEAT 2	HEAT 2, developed by Blocon AB [70], is software used for two-dimensional transient and steady-state heat transfer. The thermal bridges in this study were quantified using the software.
Wikells Sektionsdata	Wikells Sektionsdata, developed by Wikells Byggberäkningar [71], is a cost calculation database used in Sweden. This study used the database when quantifying the costs of design options using a database of cost calculations.
MATLAB	Performing the data analysis and visualisation of data using the software MATLAB [72].

3.4 Data Processing Methods

Data is fundamental for the probabilistic method and quantifying uncertainties. The data types compiled and used in this study are both qualitative and quantitative. The first step was to divide data based on qualitative analysis, identifying categories or attributes needing quantitative data to perform the overall analysis. Section *4.2.3 Factor Identification* presents the results of the qualitative analysis to identify factors. For the identified factors, the process of gathering quantitative data began. The data processing method used in this study to compile, analyse, and model using data was as follows:

1) Define questions and objectives – How and for what to use the data.
2) The data gathering was performed through a literature search using the databases described in section *3.4.3 Knowledge Discovery*. The prioritisation processes of compiled data were by empirical evidence (1), theoretical calculations or modelling and simulations (2), and estimations based on experience (3).

3) When compiled, the data was structured based on the attributes and categories identified in the qualitative analysis—assessing the data's quality before using it for further analysis and decision-making.

3.4.1 Data Quality

The definition of data quality differs depending on the perspective used. One definition is that the quality of data depends on if the information fits the intended uses. The terms used to assess data quality differ, but common attributes are accuracy, precision, timeliness, reliability, and security (protection against unauthorised manipulation). The data validation and verification process in this study for assessing and ensuring the data quality used the following two steps:

1) Data validation, ensuring the data is within an acceptable range.
2) Data verification performs a check of the data to ensure that it is accurate, consistent, and reflects the intended purpose.

Part of evaluating data from objects was to identify any true-positive, true-negative, false-negative, and false-positive data. The analysis uses the dataset to identify the true-negative and true-positive outcomes in the measured data from the objects needed to evaluate the probability of failure while also identifying and correcting or removing the false-positive or false-negative objects. The process excludes data that does not pass the validation and verification steps from further analysis, i.e., if an object's attribute was missing, the object was excluded from further analysis if this could not be solved. However, the most common limitation was the lack of data. The data passing this step was then used to create a model and implemented in the simulation.

3.4.2 Transformation and Dimensionality Reduction

Dimensionality reduction focuses on combining or eliminating variables to simplify the analysis process. The data that remained after the previous steps, data quality, were analysed, and relevant data was selected based on the objectives. The transformation and dimensionality reduction process began using the selected data, i.e. instead of using the absolute values of two columns, the relative value was used such as the performance gap instead of predicted and actual EP, or the relative value between two design options instead of the absolute value of both.

3.4.3 Knowledge Discovery

The process for knowledge discovery uses literature searches to discover and gathering new information and data extraction. The scope of the literature searches was on identifying parameters impacting a building's energy balance and compiling information and data on the identified parameters. The work proceeded by analysing the compiled information and data for the factor, modelling the parameters and the models' limitations.

Performing a keyword search in several databases using the identified terms to find both national and international literature containing methods, models and data:

- SBUF: Development Fund of the Swedish Construction Industry, the Swedish construction industry's organisation for research and development ("SBUF" 2020).
- LÅGAN: a programme for buildings with low energy use and a collaborative project between the Swedish Construction Federation, the Swedish Energy Agency, Region Västra Götaland, Formas and others [74].
- E2B2: the most extensive research programme in Sweden to date in energy-efficient building and living [75]. This programme is co-funded by the Swedish Energy Agency and The Swedish Centre for Innovation and Quality in the Built Environment.
- ResearchGate: Searching for researchers and their work published in the same field.
- LUBSearch: Search tool used for aggregated searches of databases available at Lund University [76], such as Scopus and Web of Science for articles, e-books, journals, printed books, and databases.

Keywords used, such as:

> probabilistic method, risk analysis, stochastic parameters, data science, data visualisation combined with building performance simulations, energy modelling, building energy performance, uncertainty analysis.

3.5 Research Strategy

The research strategy applied to test and evaluate the developed method was the case study. A case study is the study of a phenomenon in its real-world context [20]. The case study is a suitable strategy in this project since the purpose is to test both the whole and parts of the PRA method on a building during real-world operation to validate if the PRA method can have practical use. Therefore, several case studies were performed with new approaches to the problems and a modified process to test and evaluate the research project's specific objectives (see section *1.2 Aim and Objectives)*. Described below is an overview of the case selection process and the structure of the case studies. The criteria for deciding on the case study building differs between the objectives. Mainly because of the shift in focus, from the impact of design options on the building stock to the evaluation and confidence in a single design option's EP.

3.5.1 Case Selection Criteria

Deciding on case study buildings began by defining the case selection criteria based on objectives in section *1.2 Aim and Objectives*. The process started with deciding on three main criteria: expanding, testing, and validating the method. The identified criteria consider several perspectives, i.e. the study's aim and other limiting factors such as time, cost, and quality. From the perspective of:

- **Expanding the method** by deciding on a building with an appropriate level of complexity and size was important.
    - **For objective I:** Multiple types of buildings, representative of the period when built.
    - **For objective III:** A single building design, built multiple times to validate the model.
    - **For objective IV:** increasing the number of zones, adding new parameters, and increasing the number of stochastic parameters using a multi-family building compared to the earlier studies using a single-family house.
- **Testing the method** uses a BPS tool to create a mathematical model for a building. Thus, based on the tool used, selecting a case study building should be based on the potential of modelling the case building’s geometry, the building envelope properties, and the HVAC system in the BPS tool and ascertain and acquire a high-quality output. With modern BPS tools, this is not a limiting factor. However, because of the need for multiple simulations to quantify the probability and the computational limitation of the available hardware, a relatively small and straightforward case building is preferable to limit the time of each simulation.
    - **For objective I:** Small building, model - high level of detail, manual updating, extensive testing of design options.
    - **For objectives III & V:** Small building, model - low level of detail, automatic updating, two design options.
    - **For objective IV:** Large building, model - medium level of detail, one design option.
- **Validating the method** requires a case study building with a building typology built several times, preferably in the exact geographical location, measured EP, and data available for collection and analysis. These are

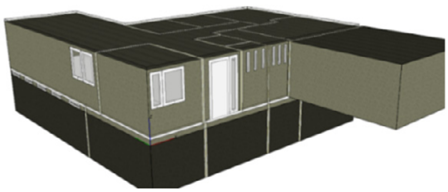
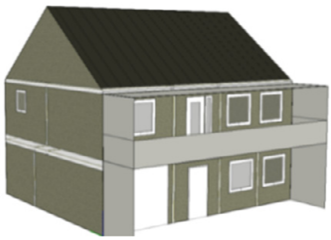
severely limiting factors for the available buildings to use. A minimum level of quality control to erase some uncertainties with the quality of workmanship is also preferable and gives some insight into how the occupants have used the buildings.

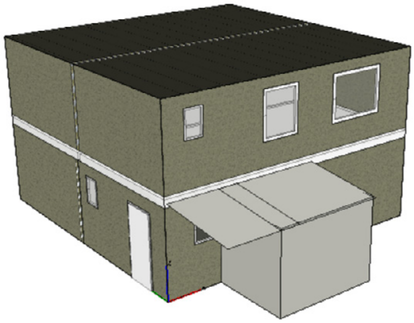
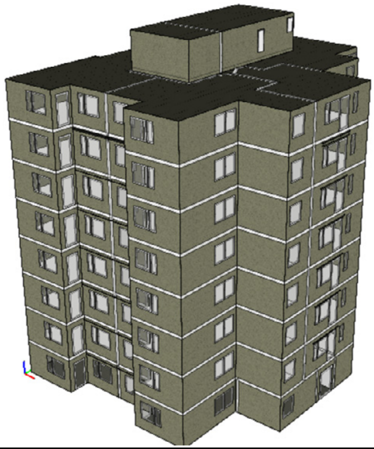
- **For objective I:** Four building designs, illustrating the common types of building built during the period, capturing the design and performance of the building stock.
- **For objectives III & V:** Single building design, built multiple times, single location.
- **For objective IV:** Single building design, built multiple times, various locations.

3.5.2 Case Studies – Selected Buildings

Several buildings have been used in the case studies to evaluate specific research questions during the research project. Table 4 presents a figure for each of the 3D models of these case buildings.

Table 4. Case buildings
An overview of the different case buildings used for each objective, using an illustration of the 3D models.

Objective	Paper	Building model	Source
I	*Paper I, IV, V, and VI*		[1], [9]
	Paper IV and V		
	Paper IV and V		

	Paper I, IV, V, and VI		
III & V	*Paper III & VIII*		[77]
IV	*Paper II*		[2]

First Phase: Building Stock Potential, Single-family Houses - During the first phase of the research project, the focus of the study was on renovating single-family houses and using BPS to evaluate the cost-effectiveness of passive house renovations. Analysing the building stock to identify representative buildings resulted in four different single-family house typologies to use in the continued investigation of passive house renovations presented in the studies (*Papers IV* and *V*). However, in the follow-up studies (*Papers I* and *VI*), the case buildings were reduced to only two due to the time and resources needed when including additional parameters. However, it was a theoretical study, presenting only simulated output since the evaluation was the relative impact of different solutions.

Second Phase: Uncertainty Analysis, Single-family Houses & Multi-family Houses - For the second half of the research project, the focus was on developing a method to quantify the risk of building designs in newly constructed buildings.

The performance gap is quantified using predicted EP from the method, and a comparison is made against measured data for actual EP collected from buildings.

To enable the comparisons requires a case building based on a design used more than once to gather statistical data to compare the simulations' probabilistic output. The process for identifying case buildings resulted in two different building designs used in the continued process: a single-family house (Objective III and V in Table 4, *Paper III* and *VIII*) and a multi-family house (Objective IV in Table 4, *Paper II*).

3.6 Verification and Validation Process

The verification and validation process was twofold; firstly, the results were compared to empirical data – when possible – and, secondly, the process and method used to acquire the results was presented so that other researchers can review and replicate the results. The second part focused on presenting the results and a detailed description of the process and input data used to acquire the results in scientific journals, where the papers have been subject to a scientific review process.

For the first part, the process differed between the case studies. In the first phase, no performance data for the specific buildings were available. Instead, the study used relative values, comparing the predicted performance before and after implementing a solution.

In the second phase, the simulations for the case study using the single-family houses was not performed in a double-blind process since the compilation and analysing process was completed earlier. However, the data resolution was coarse, reducing the analytical potential by only comparing the aggregated total. Thus, one purpose with the multi-family house was to increase the resolution to enable additional analytical comparisons.

The case study process for the multi-family building follows a double-blind setting not to affect the study's outcome and introduce additional biases when evaluating and interpreting the results. Thus, the process starts with performing the simulations and analysing the results before compiling and analysing the field measurements.

3.6.1 Field Measurements

The simulations' outputs were compared to measured data from field measurements to validate the methods and models. In the case of the single-family buildings in the first phase, the aim was to evaluate the potential for energy-saving measures in the building stock, not a specific building. Thus, as mentioned earlier, analysing the building stock to identify representative buildings resulted in four different single-family house typologies to use in the continued investigation of passive house renovations presented in the studies.

In the case study using the newly built neighbourhood of identical single-family passive houses, *Paper VIII* [8], the case building was investigated previously by Fahlen et al. [55]. Hence, field measurements were already compiled and used as a basis for the validation in this study.

In the case study of the multi-family buildings, the compiled data came from an internal NCC database comprising buildings built by NCC. However, since several objects did not have the final report - stating the measured EP after two years - the data was semi-structured. Thus, significant work was needed to gather and structure the data. Another dimension that significantly increased the difficulty of structuring the data was that the objects were in various locations spread across Sweden. The compiled data from the objects required several normalisation steps before using them to validate the simulations. This study's focus on a building stock – instead of a single building – enabled the validation against measured data from a building stock of several buildings based on the same building design. Thus, for comparison, the input data for the simulations were also based on a building stock. Using a building stock introduces several unwanted effects on the collected field measurements alleviated by a normalisation process.

A normalisation process is required to reduce or eliminate the effect of unwanted factors from the data. The unwanted factors to be removed differ depending on the data and the purpose of the models or validations. For example, for the field measurements in the multi-family house, the primary factor to be removed was the objects being located in various geographical locations and thus differing climate. Another effect was that the measured data were from different periods, and the weather differs from year to year. Other unwanted factors outside the modeller's control were the occupant activities and behaviour; however, these will always be present even in a single building, although out of the control of the modeller and building contractors. However, considering the effect is necessary when predicting the EP.

4 Results and Discussion

This chapter begins with an overview of the developed method, describing the steps required to perform a probabilistic risk analysis, and after the overview is a detailed description of the process used to develop the method.

4.1 Developed Method for Probabilistic Risk Analysis

The developed method for performing a probabilistic risk analysis of a building design's EP consists of six steps, each including different sub-steps or processes required to continue to the next step, with an overview shown in Figure 5.

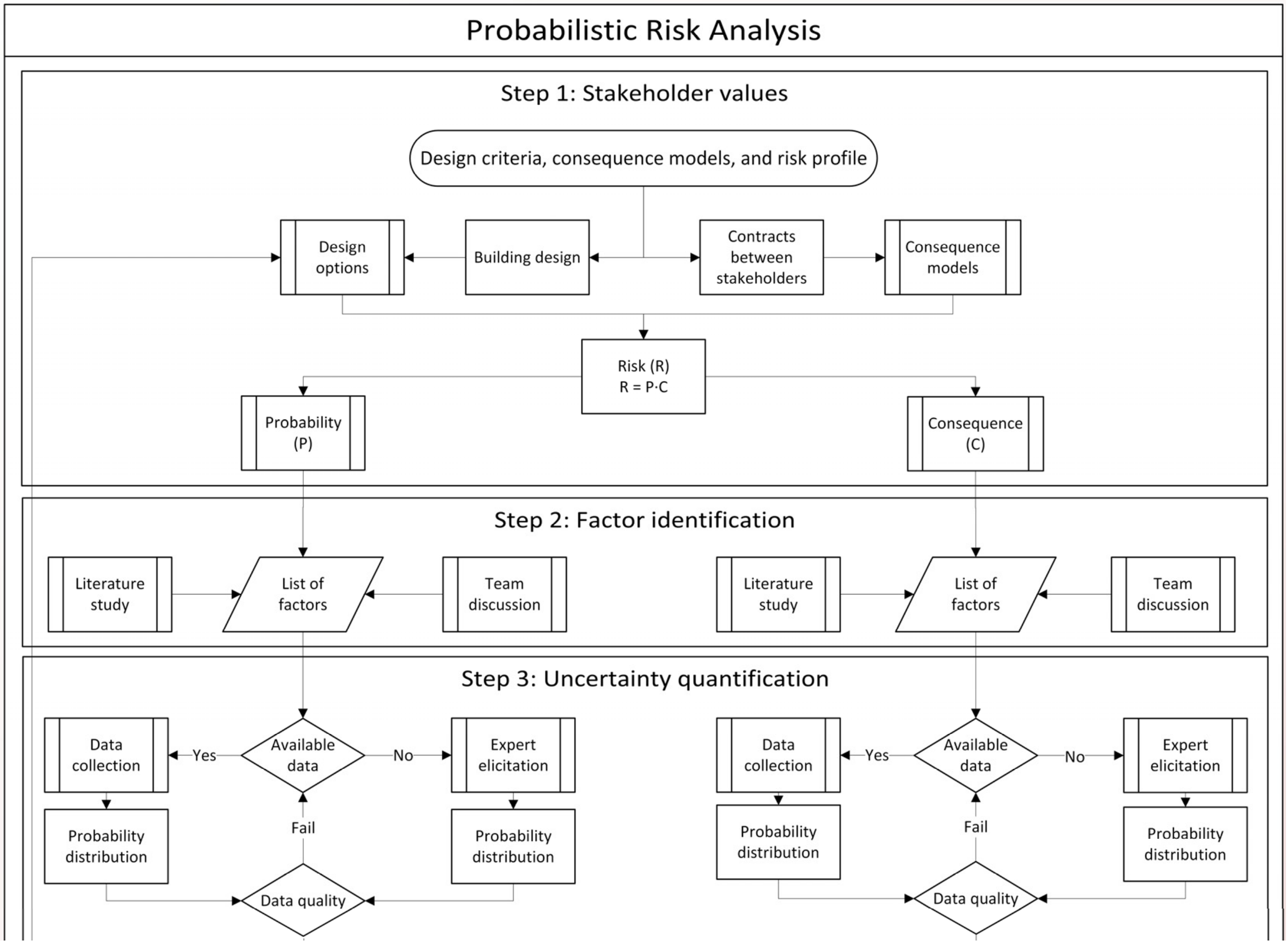
The first step, *Stakeholder values,* includes identifying and defining stakeholders and their values, providing the boundary conditions for the analysis, and determining the analysis's objectives. The step includes the design criteria that the building design needs to fulfil, the overall building design and possible design options to evaluate, the consequence model of the contract between stakeholders, and the risk profile to quantify the risk analysis's probability and consequence.

The second step, F*actor identification,* includes identifying influencing factors - and the underlying uncertainties that influence these factors - impacting the models used to quantify and evaluate if a building design fulfils the set objectives from the first step. The result of the second step is a list of compiled factors.

The third step, *Uncertainty quantification*, uses the list of factors as a basis for the uncertainties that need to be quantified. The result is a probability distribution for each identified uncertain parameter.

The fourth step, *Input data sampling*, uses the Monte Carlo method and random sampling from the probability distributions to generate the input data set used for (1) the simulations that quantify a predicted EP and (2) the consequences of failing to fulfil the design criteria.

The fifth step, *Simulations*, uses the sampled data set to perform multiple simulations and calculations, depending on the chosen models, resulting in two datasets per design option: (1) distribution of probable EP and (2) distribution of probable costs based on the variation in EP and other stochastic parameters of the consequence model.


Probabilistic Risk Analysis
Step 1: Stakeholder values
Design criteria, consequence models, and risk profile
Design options
Building design
Contracts between stakeholders
Consequence models
Risk (R)
R = P·C
Probability (P)
Consequence (C)
Step 2: Factor identification
Literature study
List of factors
Team discussion
Literature study
List of factors
Team discussion
Step 3: Uncertainty quantification
Data collection
Yes
Available data
No
Expert elicitation
Probability distribution
Fail
Probability distribution
Data quality
Data collection
Yes
Available data
No
Expert elicitation
Probability distribution
Fail
Probability distribution
Data quality

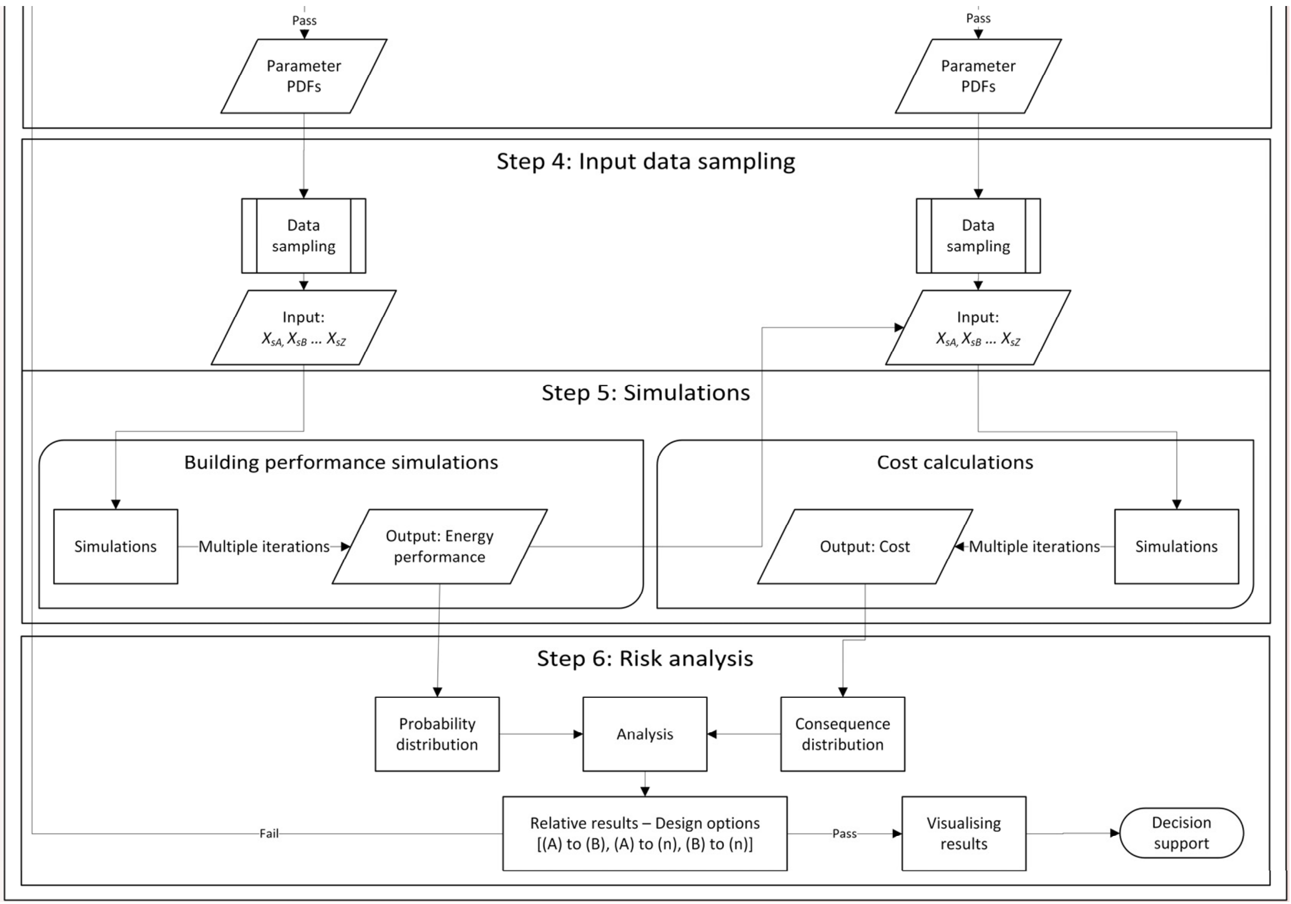


Figure 5. Overview of the developed method.
Shows the steps and processes used to quantify the risk level using the developed method.

The sixth step, *Risk analysis,* uses the resulting datasets for probability and consequence to quantify a probability for failure, the consequence of failure and a risk level for the building design. Visualising the results provide information on the risk of options and enables informed decision-making.

Paper III presents a detailed description of the steps, including a demonstration of the method using a case study showcasing how to use the method and how the method supports the decision-makers.

4.2 The Process for Developing the Method

Developing the method followed the study's objectives as described in section *1.2 Aim and Objectives*. The first step in developing the method was to apply and test current methods used to quantify the cost and EP of buildings and apply the results to guide the decision-making process during the design phase in a building project. The design of the study was to answer objective one, which was:

> Evaluate and test quantitative deterministic methods for EP and cost analysis to find a cost-effective EP level throughout the design space, highlighting advantages and disadvantages with current methods.

Research to fulfil the first objective (*Paper I & IV*) resulted in developing a method for building design evaluation with the implementation of LCC-analysis and tested in a comprehensive case study focusing on extensive energy renovation of single-family houses built in the 1960s and 1970s. The method was applied using deterministic methods for BPSs to quantify the effect of extensive energy renovation packages on EP. The focus was on the whole design space, represented by including different performance levels and solutions for improving the efficiency of the building envelope and HVAC system, using different types of heating systems, and installing a photovoltaic system, with or without energy storage solutions. The study showcases how deterministic methods for BPS produce a decision-basis for the stakeholder. However, the limitations with the deterministic methods are also evident, with the time spent on producing data from manually creating and handling hundreds of models. The study applied the LCC analysis method to evaluate different design options, identify the cost-effective options, and show how the existing building's condition impacted the cost analysis results. This first step showcased the potential and limitations of the current method for BPS in evaluating the design space and quantifying the EP and costs of different design options.

An explorative phase followed, identifying alternative methods and comparing these to the traditional deterministic approach based on the knowledge gained. Finally, qualitative methods were used to evaluate and discern when and for what purpose the alternative probabilistic methods might be advantageous to apply. Thus, the design of the study was to answer objective two, which was:

> Investigate the advantages and disadvantages of deterministic and probabilistic methods, focusing on differences in the use of sensitivity and uncertainty analysis

Investigations to fulfil the second objective began by describing the deterministic and probabilistic concepts regarding uncertainty analysis of buildings' EP, intending to identify each method's advantages and disadvantages (*Paper VII*). Throughout the research project, the work defined related concepts and methods to improve the analysis's accuracy and quality (*Paper II and III*). The study presented in *Paper VII* discussed the difference between handling risk using a margin of safety for deterministic methods and the probability of failure for probabilistic methods, as illustrated in Figure 6.

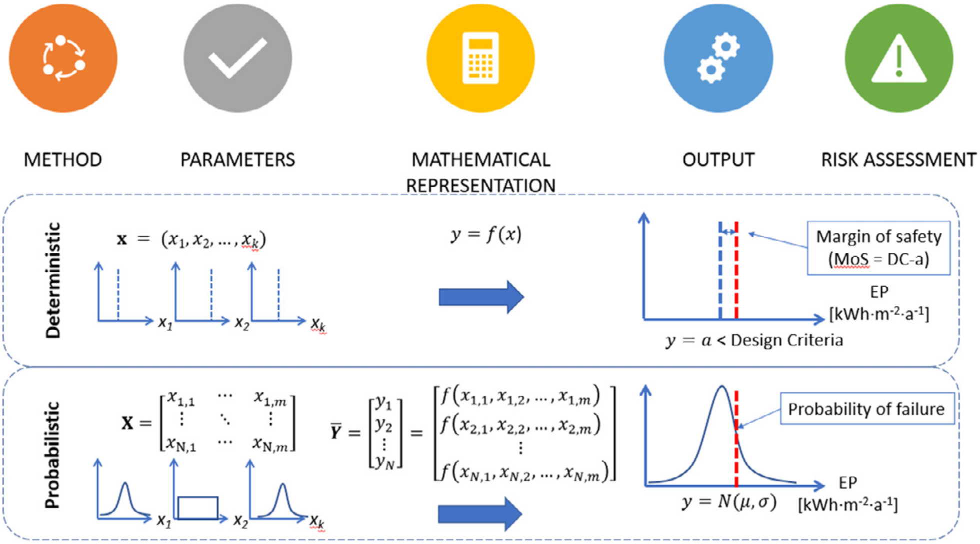


Figure 6. Overview of the deterministic and probabilistic methods.
Presents an overview of the deterministic and probabilistic methods and illustrates the differences in handling input data, modelling, and results.

After identifying the advantages of the probabilistic approach, the next step was to develop a method for implementing the probabilistic approach for EP and risk analysis. The design of the study was to answer objective three, which was:

> Develop and demonstrate a probabilistic risk analysis framework for BPS, using a probabilistic approach to quantify probability and consequence, allowing for evaluating building design options

The process began with developing and testing an experimental method for PRA, presented in *Paper VIII*.

The focus was on using the probabilistic approach to quantify the EP and probability of failure and expanding the method into a risk analysis method. The results indicated the need to investigate how the accuracy of the predictive model influences the robustness of the predictions.

A method was needed to quantify the consequences to enable the PRA. The first version (*Paper VIII*) of the method was developed based primarily on the building contractor's stakeholder viewpoint and using a case study with a project agreement that includes a design criterion based on EP contracting, as illustrated earlier in Figure 1. The building contractor's stakeholder viewpoint enables the use of the concept of value-at-risk to quantify consequences.

After developing the first version of the experimental method, the next step was to evaluate the prediction model's dependence on data, previously identified as a significant limitation for implementing the probabilistic approach in the previous phases. Finally, the design of the study was to answer objective four, which was:

> Investigate the impact of data quality on the accuracy of the predictive model

Based on the concept of accuracy - using the definition from ISO 5725 illustrated in Figure 7 - the impact of data quality on accuracy was evaluated using a case study and quantified this using two datasets, based on different quality levels, presented in *Paper II*. For a detailed definition of the data quality level, see the paper.

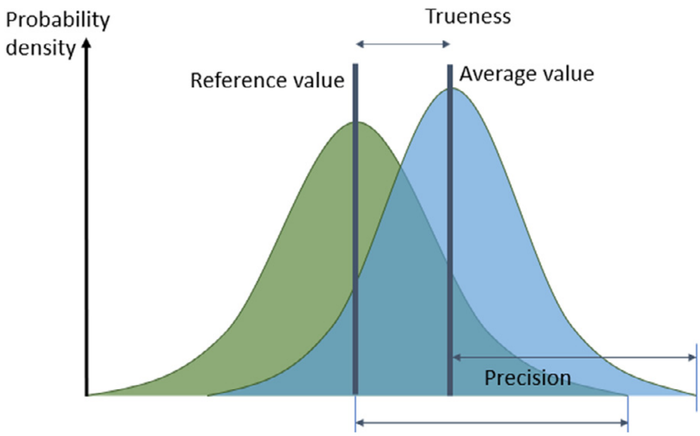


Figure 7. Concept of accuracy
Illustration exemplifying the trueness and precision of the outcome compared to the reference value based on the terminology from ISO 5725.

In the study presented in Paper II, a case study applied the method to multi-family buildings, increasing the building models' complexity and the number of input parameters. This paper discussed the impact of the used level of detail on both the building model and the input data and analysed the impact on the accuracy of the predictive model, the risk analysis, and the risk level. Part of the results from the theoretical study presented in *Paper II* was also a continuation of the impact of design criteria on the risk level since three different design criteria had been used for the case building with the same building design, as illustrated in Figure 8.

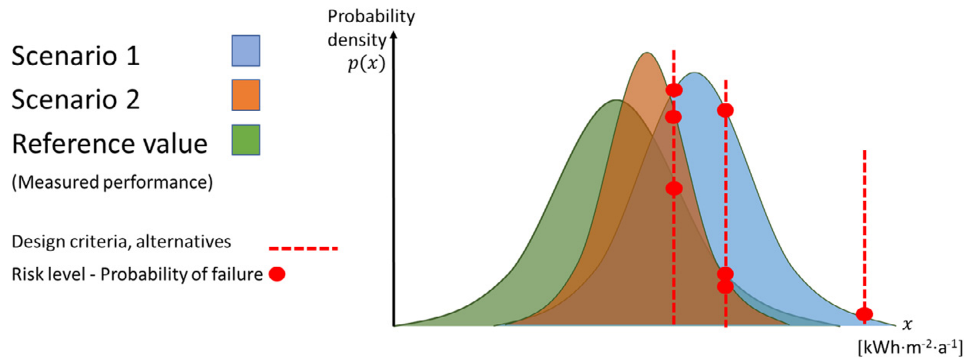


Figure 8. Concept of accuracy and the impact of the design criteria
Illustration of how the accuracy was investigated using two scenarios (datasets) based on different data quality and validated against measured data from field measurements. Also, how this influences the probability of failure.

The development of the method continued by including different stakeholders, models for consequences, and applied the method for design optimisation by including alternative design options in *Paper III*, and illustrated in Figure 9. The process required a definition of risk, followed by the quantification of consequence, and developing visualisation of the risk level to improve the decision-making process when designing a building to fulfil the design criteria. The design of the study was to answer objective five, which was:

> Explore how to integrate the analytical results from the PRA for BPS into the decision-making process during the design phase using visualisations.

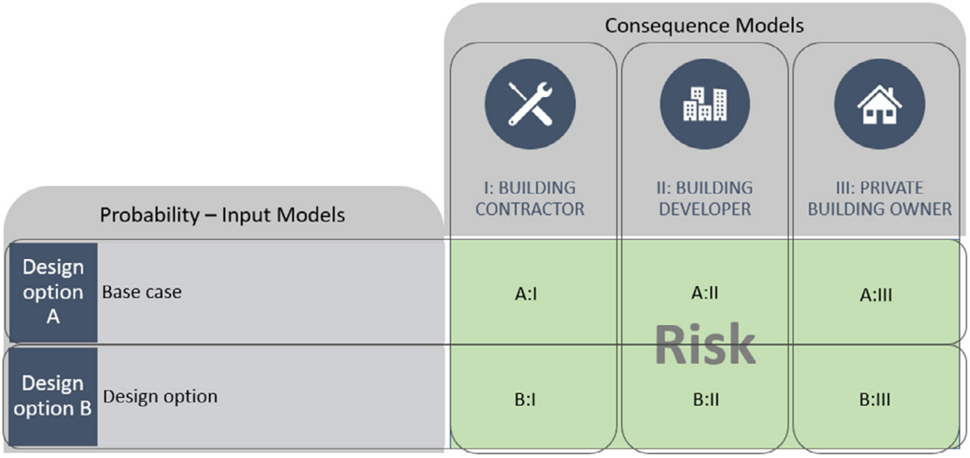


Figure 9. Overview of the design options and consequence model in *Paper III*.
Illustrating the various design options (A and B) evaluated showcasing the impact on the probability of failure and the used stakeholders' (I, II, III) to show the difference in impact on the quantification of consequences. Combining these alternatives resulted in a risk level.

Based on the knowledge gained in *Paper I*, the LCC analysis method was implemented in the risk analysis process of *Paper III* to improve the quantification of consequences developed in *Paper VIII*. Implementing a probabilistic approach for the LCC analysis expands the method to include both parts of the risk concept. The study presented in *Paper III* continues the work from *Paper VIII,* expanding the model for quantifying consequences to incorporate stakeholders' specific conditions and adding two more stakeholder viewpoints, the private homeowner and the professional property developer. The study presented in *Paper III* aimed to integrate the PRA for BPS into the decision-making process during the design phase from different stakeholder perspectives and use different visualisations to communicate the results.

4.2.1 Risk Analysis for Building Performance Simulations

The next step was to develop the method for probabilistic risk analysis by applying the previously described definition of risk to the specific area of interest, the EP of buildings. Thus, the risk in question would be regarding the EP of a building and should answer the question:

- What is the risk that this building design will not fulfil the requirements regarding EP?

Two sub-questions that need answers are contained within the overall question; (I) What is the probability that the building's energy use is higher than the energy requirements?; and (II) What is the consequence if this happens? The consequences are focused costs or liabilities that the building contractor would have to pay to compensate the developer for the increased operational costs. There could also be legal liabilities depending on the outcome, including additional costs depending on the requirements. Question I is answered by identifying the parameters that impact energy use and defining each distribution and probability. Then the energy use is simulated for these variations. The results are then a distribution of the probability for energy use. Question II is answered by identifying the consequences of not fulfilling the energy requirements as these often depend on the specific project and contract, i.e. by defining:

- If the building contractor is required to operate the building for a specific period, the tender needs to include the operating cost.
- If the building does not fulfil the energy requirements, the building contractor must rectify this, regardless of the measures or costs required.
- An EP contract, where the building contractor either pay a specific sum or covers the extra operating costs until the problem is corrected or during a specific period.

There are many types of risks and uncertainties involved in a construction project. The uncertainties could include the design, simulations and calculations, products, construction, operation, maintenance, workmanship and extrinsic factors such as interest rates, energy costs, policies and more. The input data used in the simulations are a significant risk factor, primarily because the actual occupants' behaviour deviation from the assumed.

4.2.2 Scope of Analysis

A building project's system boundaries and design conditions determine which approaches to use and at what phase of the building process. Examples of the design conditions set by the building developer are the relevant regulatory framework or a more stringent condition from an internal or external assessment method for rating and certifying a building design. In addition, the design criteria and stakeholders risk profile define the acceptable risk level for all involved in the project.

Examples of questions posed in building development projects:

- Which are the most significant components to improve?
- Which design of a component to choose?
- What is the optimal combination of components and systems?
- Does the simulated building design under fixed conations fulfil the design criteria?
- What building design is the most cost-effective?
- How likely is this building design to fulfil the energy design criteria?

- How likely is the measured EP of the actual building to fulfil the energy design criteria?

Depending on the question posed, different analytical perspectives and methods are applied; examples of these are:

- Deterministic vs probabilistic approach
- Explorative – diverging and converging phases
- Benchmarking (theoretical) vs actual
- The margin of safety vs probability of failure
- Sensitivity (component effect on outcomes) vs uncertainty analysis
- Scale - component vs building vs building stock
- Optimization of building design vs risk analysis of specific design options

When the scope of the analysis is determined, questions regarding how to perform the analysis emerge; these need to focus on aspects such as; data, data quality, modelling, level of detail of models, and spatial and temporal resolution of data.

4.2.2.1 Scale and Purpose of Analysis

Within the field of uncertainty analysis, there are several options for methods to apply. Before deciding on the methods to use, it is necessary to decide the analysis's scale and purpose. The scale and purpose decide the method to apply to the problem and create the building model. The scale refers to the scope of the system analysed, from a small scale - such as a component or product – to a large scale – e.g. a cluster of buildings or building stock. The chosen scale decides the scope of uncertainties needed to quantify and model and the building model's complexity. The purpose refers to whether the prediction model predicts the actual EP or optimises the building design. The purpose decides the prediction model created and determines the sampling method for sampling the input data. There are several methods available for the sampling of input data for uncertain parameters. A review study by Tian et al. [25] describes available methods and motivations for using them.

4.2.3 Factor Identification

As part of the case studies and developing the method, a conceptual building was decomposed into systems, elements and factors influencing the performance. The performed factor identification step during the studies resulted in the tree hierarchy shown in Figure 10. Figure 11 shows a zoomed-in example. Based on these factors, the process continued to the next step of uncertainty quantification based on the identified factors. The quantified uncertainties were on different levels in the tree structure, thus either categorised as main parameters or sub-parameters, where the sub-parameters are combined to quantify the total uncertainty of the main parameter.

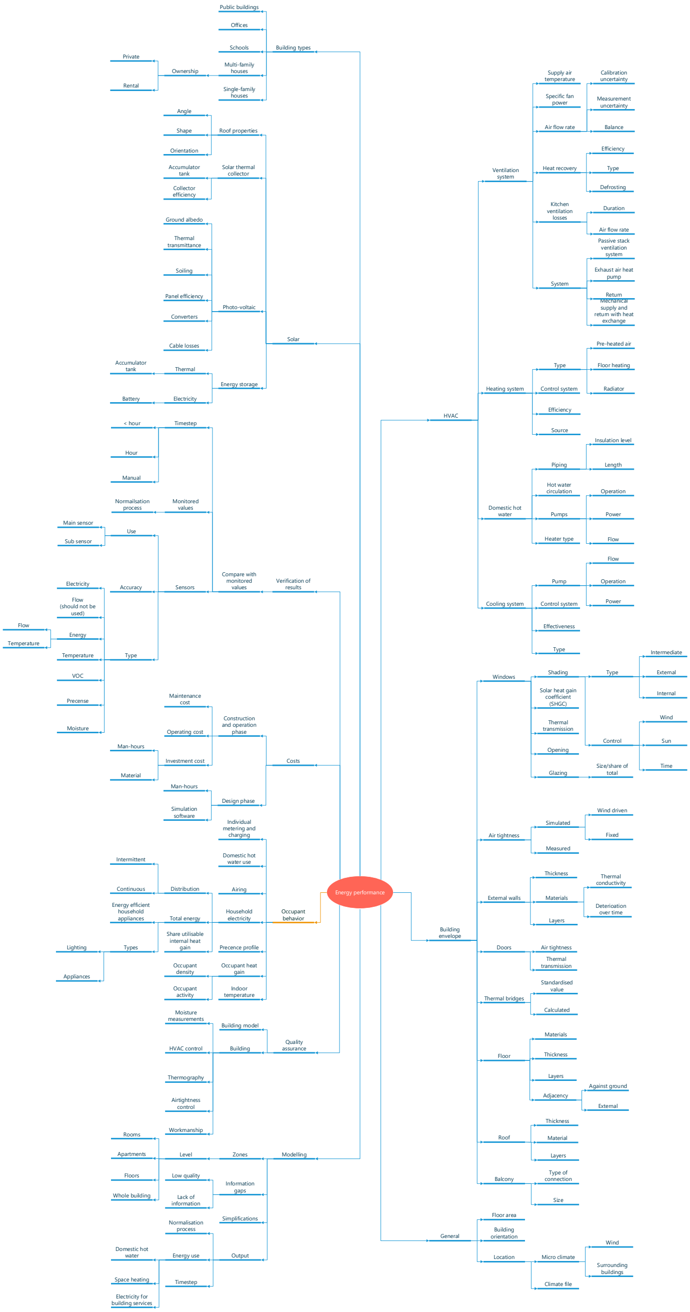


Figure 10. Overview of the result from the factor identification step (not readable, illustration purpose only). The figure shows all the factors identified impacting the EP of buildings during the design, construction and operational phases. The figure below presents an example of a more detailed branch.

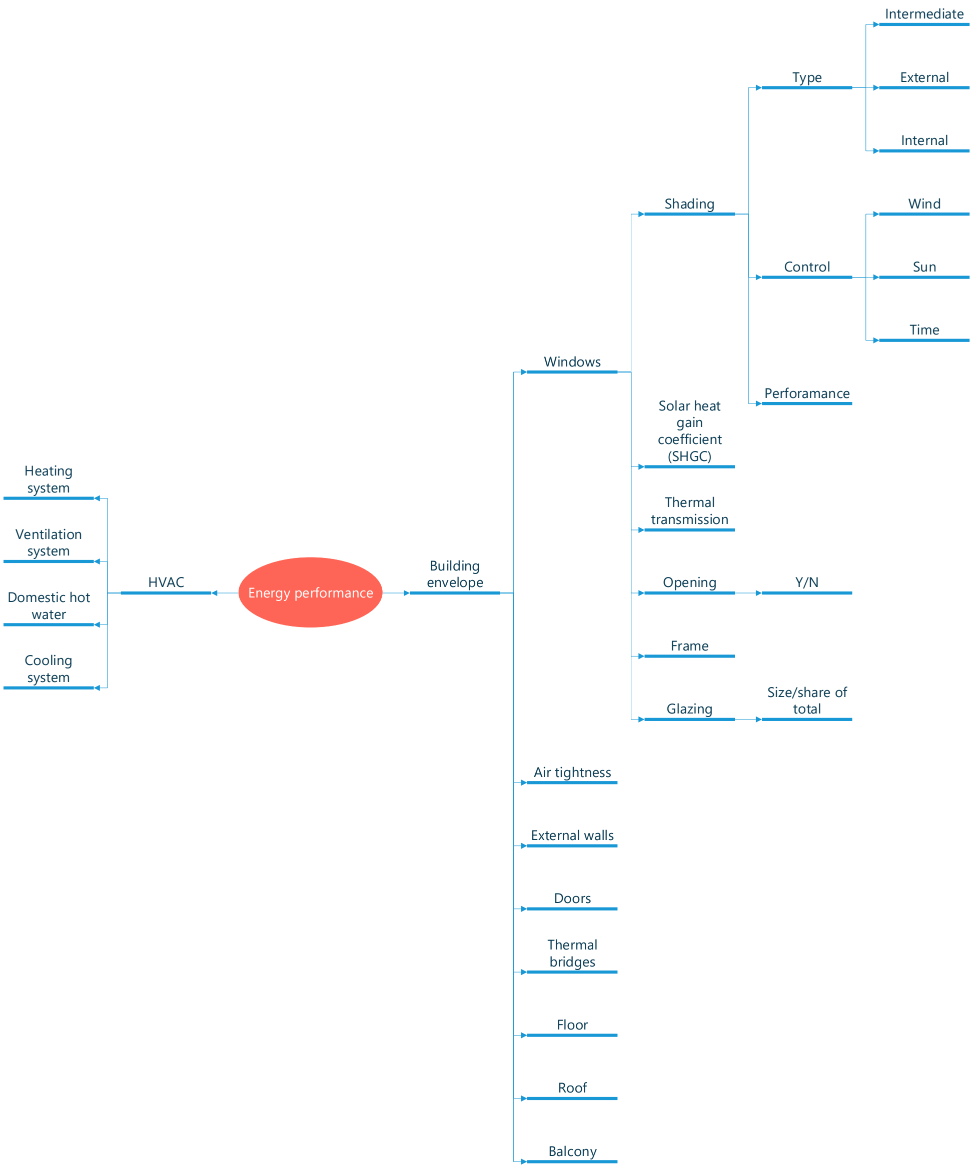


Figure 11. Example of a branch from the overview of the factor identification in Figure 10.
This branch shows how the factor identification process uses the decomposition method of breaking each parameter into sub-parameters.

The identified factors were categorised based on whether they were included deterministically or probabilistically in the model. If included probabilistically, also included is a description of the type and source of uncertainty. The last categorisation was if the parameter is included internally in the building model and simulation or externally in the post-processing. Table 5 shows an example of how the parameters are listed. The next step uses the list of probabilistic parameters as input for the uncertainty quantification process.

Table 5. Illustrating the structure for categorising uncertain parameters.
A matrix containing examples of parameters categorised based on the type of uncertainty, type of input, and how to include the parameters in the building model.

	Uncertainties, types of				Input		Modelled	
Stochastic Parameter	Modelling	Scenario	Design undecided	Design decided	Determ.	Prob.	Internal	External
Parameter - A	x	x	x			x		x
Parameter - B		x	x		x			x
Parameter - C	x	x		x		x	x	

4.2.4 Uncertainty Quantification

The uncertainty quantification process was developed and described in *Paper II, III,* and *VIII* and applied in *Paper II* for parameters impacting the EP and probability of failure and in *Paper III* for parameters impacting the consequence models. For more details, see the papers. The process results are a probability density function (PDF) for each stochastic parameter of the building model quantified based on either empirical data or expert elicitation. Figure 12 shows an example of the models.

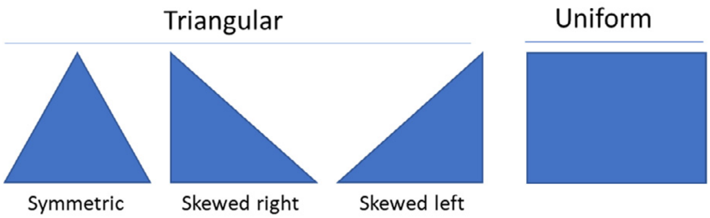


Figure 12. The shapes of the probability distributions
Illustrates the probability distributions assigned to the input data in the energy simulations of the case study, symmetrical triangular distribution (T_S), skewed triangular distribution, right (T_{SR}) or left (T_{SL}), and uniform distribution (U).

4.2.4.1 Bias, Confounding Factors, and Outliers

The input data's quality can be impacted by bias, confounding factors and outliers. These deviations in the input data can be challenging to identify. Because of the need to process the data collected before using it to determine the variance and probability of parameters, there is a risk for bias when interpreting the data. There could also be unknown confounding factors that influence the data. One confounding factor identified in the measured data from the 26 single-family houses was how the occupants used the vestibule in at least one of the houses. The vestibule was to be unheated. However, in this case, the occupants used the area so that the interior door was open so that the area was heated to the indoor temperature, increasing the building's energy use and being seen as an outlier in the measured data.

Data was compiled from multiple sources when possible when quantifying a parameter. However, the compiled datasets contain the same apparent parameters in specific cases, but the data was based on other types and sources of uncertainties or using a different parameter model. Thus, interpreting the data and ensuring that the data and model described the intended purpose were significant obstacles. Showcasing the difficulty of quantifying and modelling this parameter is the variability in the data for indoor temperature in IEA EBC Annex 55 [78], which presented measured indoor temperature from several buildings, both single-family and multi-family buildings, built in different periods, with various building systems, and in different countries. Interpreting data from others is a common problem because of differences in the documentation. Developing and proposing a solution for collecting and documenting empirical data to enable comparison and model creation is the aim of the project Building Energy Epidemiology, IEA EBC Annex 70 [79], [80], a currently ongoing project.

4.2.5 Consequences of Unwanted Events

When testing the developed method in the case studies, the process also identified several possible consequences of unwanted events regarding the EP in buildings. Exploring unwanted events used a qualitative approach, using expert elicitation based on the research group's knowledge to identify consequences. However, the continued focus was only on consequences easily quantified as a cost, applying different consequence models and stakeholders' perspectives.

4.2.5.1 Outcomes – Positive and Negative

In a practical application of risk assessment and analysis, the positive or negative outcomes affect various aspects. These aspects of risk are the financial, reputational and project risks. The following outcomes are examples from the viewpoint of EP in buildings:

Positive outcomes when applied to EP in buildings:

- Better EP than predicted.
- Lower energy use than forecasted.
- Lower operational costs than predicted.
- Positive impact on reputation – deliver the agreed-upon level in the contract.

Adverse outcomes, when applied to EP in buildings:

- Non-compliance with building regulation
- Worse EP than predicted
- Higher energy use than predicted.
- Higher operational costs than forecast.
- Negative reputation – does not deliver the agreed-upon level in the contract.

Regulation and Requirements

- All buildings need to fulfil the building regulation, although the requirements can vary depending on the project. In addition to the building regulation, the developer could include other, more stringent requirements. The consequence is defined as the building contractor's liability if not fulfilling the requirements and are described further below.

The Impact on the Reputation and Business Relations

- In addition to the liabilities, not fulfilling the obligations could also negatively impact the responsible party's reputation and the future business relationship with the developer.

Quantifiable Consequences and Models – Financial Consequences

- Although several possible consequences were identified, this research project has focused on quantifiable consequences, in financial terms, used in a cost-benefit analysis. Applying these models for economic consequence and implementing them in the developed method is presented in Paper III & VIII.

4.2.6 Probabilistic Risk Analysis

Performing the previous steps results in a quantified probability of failure and consequence of failure. What remained in the PRA process was combining these quantified levels into a comprehensible and stringent metric, enabling all stakeholders to incorporate the metric into their respective processes for building projects and provide the decision support needed for deciding on the building design. There are different visualisation tools available visualising risk. The first alternative evaluated was a probability-impact risk chart, which places an option - similar to the qualitative risk analysis presented in section *0*

Risk Analysis – Applying the Concept of Risk – in a two-dimensional space, where one axis is the probability from 0 to 100 per cent, or low to high, and the other axis is the consequence or impact, either in actual or relative cost. An example of how to use the probability-impact risk chart based on the results from the PRA was presented in *Paper VIII* and is shown in Figure 13, using two design options from *Paper III* as an example.

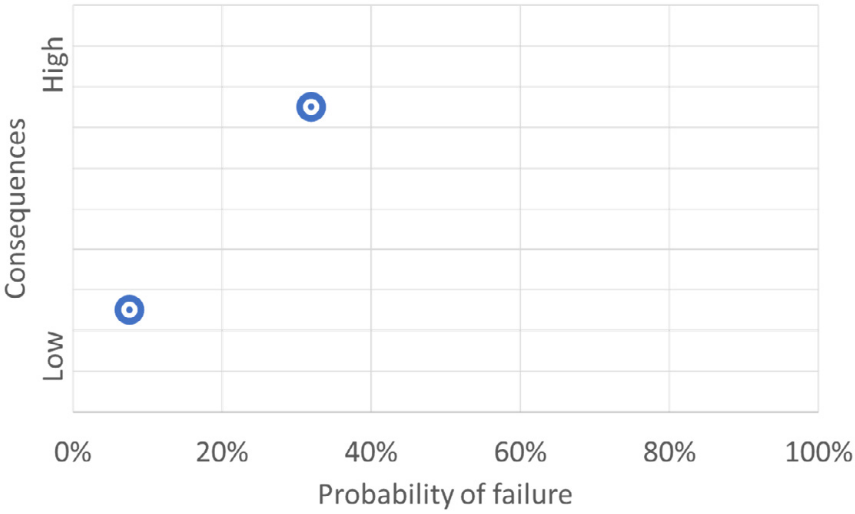


Figure 13. Probability-impact risk chart
An example of a probability-impact risk chart showing a comparison of two design options.

Although not presented using the chart, the numerical values used to create the chart were presented as a table in *Paper III* for the EPC model. Another tool for visualising the probability and consequence was tested in *Papers II and III* using the CDF plot to quantify and visualise the results. An example of this plot is presented later in the results sections, 4.3 Testing and Validating the Method. The study presented in *Paper II* uses the absolute values from the results. In contrast, the study presented in *Paper III* uses the relative values in the results from the LCC of the compared design option to quantify the probability of a design option being the financially beneficial option.

4.2.6.1 Probabilistic Approach and Changes in the Analysis Process

Using probabilistic methods adds new dimensions to the calibrations of models and analysis and evaluation of the predicted EP. For example, changing the input parameters' variance shifts the variance on a one-dimensional scale with the deterministic method. Using probabilistic methods adds another dimension to this, which requires both shifting and stretching the distributions to fit the validation data; an example of this difference is presented in section *4.4.3 Energy Performance Gap*.

4.3 Testing and Validating the Method

The developed method aims to predict the possible distribution of EP for individual buildings during the design process based on possible futures as a probability distribution. The testing and validation of the method use case studies focused on multiple buildings, using field measurements to compare EP's predicted and actual distribution to validate the method.

The developed method was continually tested and validated during the project and presented each of the steps in separate papers. The first step in the validation process was to compare the predicted EP by applying the method on single-family houses against field measurements presented in *Paper VIII*. Next was by evaluating the impact on the accuracy of the predictive model depending on the data quality used for the uncertainty quantification applied to a multi-family building and compared against field measurements, presented in *Paper II*.

4.3.1 The Probability of Failure

Performing the testing of the method and validation of the probability of failure uses two steps. The first used the single-family case-building; however, when not possible to perform a more detailed analysis regarding the deviations between the predicted and actual EP, the process continued by identifying a more suitable case building, in this case, the multi-family building.

4.3.1.1 Using the Single-family Case Building

The study presented in Paper VIII tested the proposed method using the single-family case building and compared the simulated results to the measured data from the case study buildings. Using the CDF for the simulated results and field measurements, the probability of failure was quantified, and the accuracy was tested by comparing the results (see Figure 14).

The figure shows a correlation between simulated and measured values regarding both variation and shape of the probability distribution. However, the simulated results do not include the extreme outliers found in the measured data. The results are as expected since the input parameter distributions were limited and did not include the extreme values, i.e. defined in a limited space to avoid unrealistic input values. This result confirms earlier research by Burke et al. [28] since this project uses an alternative method to replicate previous research with similar results.

The evaluation of the 26 houses in a previous study by Fahlén et al. [55] identified abnormal user behaviour was in some houses. As expected, the curves based on the simulated and measured data converge when excluding the outlier data point in the measured data. The remaining difference could likely be explained by the uncertainties currently not included in the simulations. Another likely cause is household electricity, shown to be lower than the standardised level in a recent study [81].

Comparing the results from the demonstration (P_F: 1.6 %) to the measured data (PF: 18 %) and the measured data excluding outlier (P_F: 11 %), see Figure 14. Thus, the current data and stochastic variation result in an underestimation of the probability of failure. Another uncertainty in the results is the number of simulations used and the limited data set for the measured data. Further analysis with a higher level of detail was impossible because only the EP was available in the field measurements, not the energy use for each category of space heating, DHW, and electricity for building services. Thus, a new case building and case study was needed to enable a more detailed analysis of the accuracy of the predictive model.

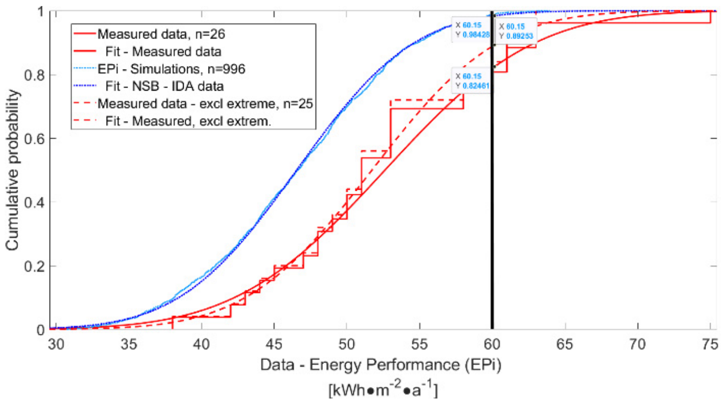


Figure 14. CDF plot for simulated results and field measurements.
The results from the BPSs (n=996) and the measured data from the 26 single-family houses, imported into MATLAB to present the data as CDF and fitted with a normal distribution. Results, probability of failure: simulated, 1.6 %, measured data 18 % and adjusted measured data, 11 %.

4.3.1.2 Using the Multi-family Case Building

An evaluation of the impact of data quality on the accuracy of the predictive model was initiated based on the results in Paper VIII. The evaluation uses the research strategy of the case study using a multi-family building. The design of the case study was to use a single building design, built multiple times to enable the comparison of accuracy between predicted and actual outcomes using different datasets. The choice of the new case building was because, in addition to the above conditions, more detailed data was available that enabled a more detailed analysis regarding the accuracy of the predictive model. Below is a summary of the datasets, results and conclusions; for more information, see *Paper II*.

Two scenarios – S1 and S2 – were used as examples to show the impact on accuracy by using various sources to compile data with differing quality and granularity and by using different models to quantify uncertainties. Thus, whenever possible, the datasets were compiled from different data sources. For example, for parameters with the building envelope and building services characteristic decided by the building design, both scenarios primarily used the design value while adding quantified sources of uncertainties to the parameters, thus changing the distribution's scaling and shape.

Scenario 1 (S1) was defined to showcase a minimum data quality level when simulating a known building design (within acceptable standards). The basis was the standardised input data from the Swedish building regulation's benchmarking system, where the deterministic models for parameters were assigned probability distributions using standardised input data and expert elicitation for the quantification process. Thus, S1 uses a combination of (1) specific design values for the building design and standardised values for parameters with an unknown design value – i.e. occupant dependent parameters - from the data sources Sveby [82] and BEN [24], and (2) expert elicitation to estimate the variation and distribution of the parameter based on the value from step 1 and the experience within the project group.

Scenario 2 (S2) aimed to improve the data quality and models for all identified uncertainties, based on specific data gathered from public sources - from studies focusing on quantifying specific parameters - and implementing existing or new data models with probability distributions. The level of detail was also increased, resulting in more parameters included on a local level (see section 4.4.1 Level of Detail).

Table 6 presents a summary of all stochastic parameters. In some cases, when creating the models for the main parameters, the variation was quantified using a combination of more than one type of uncertainty. Choosing this process for modelling enabled updating the distributions as new types and sources of uncertainties for a parameter are identified, quantified, and included in the study.

Twenty-two main parameters were identified, with an additional six sub-parameters for S1 and 11 sub-parameters for S2, assigning the same sub-parameters to multiple main parameters. The sampled input data includes additional distributions since several parameter uncertainties were included on the local level, sampling a value for each zone from the probability distribution. The parameters are described in Table 6 by the level of detail included in the building model (*L* = local, *G* = global), the units of the variation and the distribution shape and scaling used in each scenario. The distributions are described either by **U**[*a,b,c*], a uniform distribution, or **T**[*a,b,c*], a triangular distribution, with minimum value *a*, maximum value *c*, and the design value (mode) *b*, or - in specific cases - **S**, using models developed in other studies for the shape and distribution. The specific models, **S**, are explained in more detail below for the specific parameter.

Table 6. Quantified stochastic parameters.
Summary of the stochastic parameters and the quantified types and sources of uncertainty, described by how included in building model (G=Global, L=Local), and the shape of the distribution (T, U or S) and the variation (min, design, max values) for both scenarios (S1 and S2).

	Scenarios			**S1**	**S2**
	Parameter	G/L	Unit		
Building envelope	Heated floor area, A_{temp}	G	m^2	T [2399, 2448, 2497]	T [2519, 2570, 2621]
	Mineral wool, thermal conductivity	G	$W \cdot m^{-1} \cdot K^{-1}$	T [0.032, 0.038, 0.044]	T [0.032, 0.038, 0.044]
	Windows, thermal transmittance, U_w	G	$W \cdot m^{-2} \cdot K^{-1}$	T [1.00, 1.10, 1.30]	T [1.00, 1.10, 1.30]
	Shading	G	-	T [0.40, 0.50, 0.60]	T [0.40, 0.50, 0.60]
	Solar Heat Gain Coefficient (SHGC)	G	-	T [0.49, 0.52, 0.55]	T [0.49, 0.52, 0.55]
	Thermal bridges	-	-	-	-
	%, of total thermal transmission of envelope	G	%/100	U [0.15, 0.20, 0.25]	-
	External slab / external wall	G	$W \cdot m^{-1} \cdot K^{-1}$	-	T [0.12, 0.23, 0.34]
	External wall / internal slab	G	$W \cdot m^{-1} \cdot K^{-1}$	-	T [0.08, 0.09, 0.10]
	External Windows & Doors perimeter	G	$W \cdot m^{-1} \cdot K^{-1}$	-	T [0.02, 0.03, 0.05]
	Roof / external walls	G	$W \cdot m^{-1} \cdot K^{-1}$	-	T [0.07, 0.12, 0.16]
	Balcony floor / external wall	G	$W \cdot m^{-1} \cdot K^{-1}$	-	T [0.28, 0.39, 0.51]
	External wall / external wall	G	$W \cdot m^{-1} \cdot K^{-1}$	-	T [0.13, 0.14, 0.15]
	Airtightness, q_{50}, external surface at ± 50 Pa	G	$l \cdot s^{-1} m^{-2}$	T [0.10, 0.30, 0.50]	T [0.10, 0.30, 0.50]
	Built-in moisture	G	$kWh \cdot m^{-2} \cdot a^{-1}$	T [1.5, 3.3, 5.1]	T [1.0, 2.2, 3.2]
Air handling unit	Specific Fan Power - Supply air	G	$kW \cdot m^{-3} \cdot s$	T [0.75, 0.75, 1.05]	T [0.75, 0.75, 1.05]
	Specific Fan Power - Exhaust air	G	$kW \cdot m^{-3} \cdot s$	T [0.75, 0.75, 1.05]	T [0.75, 0.75, 1.05]
	Heat recovery efficiency	G	%/100	U [0.77, 0.80, 0.83]	U [0.77, 0.80, 0.83]
	Return airflow	-	-	-	-
	Measurement uncertainty	L	%	T [0.9, 1.0, 1.1]	T [0.9, 1.0, 1.1]
	Calibration uncertainty	L	%	T [0.9, 1.0, 1.1]	T [0.9, 1.0, 1.1]
	Supply airflow	-	-	-	-
	Unbalanced	L	% /100	T [0.03, 0.05, 0.07]	-
	Measurement uncertainty	L	%	T [0.9, 1.0, 1.1]	T [0.9, 1.0, 1.1]
	Calibration uncertainty	L	%	T [0.9, 1.0, 1.1]	T [0.9, 1.0, 1.1]
	Supply air temperature setpoint	G	°C	T [18.0, 19.0, 20.0]	T [18.0, 19.0, 20.0]
Heating- and control-system	System efficiency - Space heating	-	-	-	-
	Plant losses	G	%/100	U [0.05, 0.10, 0.15]	U [0.05, 0.10, 0.15]
	Distribution losses	G	%/100	U [0.03, 0.05, 0.07]	U [0.03, 0.05, 0.07]
	Domestic Hot Water circulation losses	G	$kWh \cdot m^{-2} \cdot a^{-1}$	T [2.0, 4.0, 6.0]	T [2.0, 4.0, 6.0]
	Indoor temp. setpoint - Residential	-	-	-	-
	Adjustment uncertainty	L	°C	T [-0.5, 0.0,0.5]	T [-0.5, 0.0, 0.5]
	Occupant controlled setpoint	L	°C	21	T [21, 22, 23]
	Indoor temp. setpoint – Non-residential	L	°C	T [17.5, 18.0, 18.5]	T [17.5, 18.0, 18.5]
Occupant	Household electricity	L	$kWh \cdot m^{-2} \cdot a^{-1}$	T [20.0, 30.0, 40.0]	S [2, 23, 102]
	Share utilisable internal heat gain	L	%/100	-	T [0.70, 0.75, 0.80]
	Domestic hot water	G	$kWh \cdot m^{-2} \cdot a^{-1}$	T [15.0, 25.0, 35.0]	U [5.0, 14.5, 24.0]
	Kitchen ventilation losses	G	$kWh \cdot m^{-2} \cdot a^{-1}$	T [1.0, 2.0, 4.0]	T [1.0, 2.0, 4.0]
	Airing losses	G	$kWh \cdot m^{-2} \cdot a^{-1}$	T [3.0, 4.0, 5.0]	T [3.0, 4.0, 5.0]
	Heat gain – number of occupants	-	-	-	-
	Residential - 2 R&K	L	*N*/zone	T [1.19, 1.63, 2.07]	T [1.19, 1.63, 2.07]
	Residential - 3 R&K	L	*N*/zone	T [1.74, 2.18, 2.62]	T [1.74, 2.18, 2.62]

4.3.1.3 Accuracy of Simulations and the Impact on the Risk Level

The results from the simulations and field measurements from the objects are presented as PDFs and CDFs to evaluate the impact on accuracy from the changed data quality of S1 and S2; see Figure 15 and Figure 16. Figure 16 presents an example of using the design criteria to evaluate the impact on the risk level and how this influences the decision-making process. The example in Figure 16 shows how to determine the probability, using the design criteria for EP, represented by vertical lines starting from the design criteria value on the horizontal axis up to the curves and then vertical lines out to the vertical axis. The simulated results for the EP show that, compared to the measured EP, the predictive model's accuracy increased with S2 compared to S1, regarding both the trueness and precision. However, both S1 and S2 deviated significantly regarding the trueness compared to measured data.

The hypothesis proposed was that the cause for the deviation could be due to the inclusion of external parameters – not included dynamically in the simulations – for the parameters impacting space heating: airing losses, built-in moisture, and kitchen ventilation losses. After removing these parameters from the results of S2, another comparison was made, see Figure 15. The results showed a significantly increased trueness compared to measured data, slightly reducing the precision.

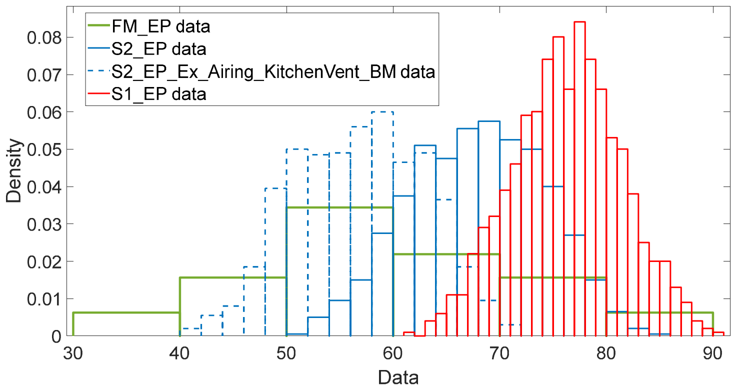


Figure 15. Results from the simulations and field measurements
PDF of EP based on measurements and simulated results using S2 and S2 without external parameters compared to measured data, FM. The horizontal axis shows the EP in kWh·m^{-2}·a^{-1}.

The probability of failure was calculated using the different predictive models – created based on the outcomes from the four options; S1, S2, S2 - without external parameters, and field measurements – and using the various design criteria to evaluate the models' accuracy (see Figure 16 and tabulated values in Table 7).

Comparing the risk level of the predictive models to the field measurements indicates that the current predictive models based on the two datasets are not accurate enough to predict the probability of failure. Currently, S1 and S2 overestimate, while S2 without external parameters underestimates the probability.

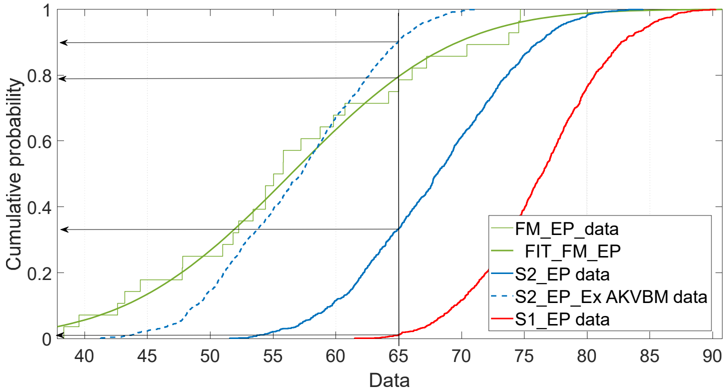


Figure 16. Quantified probability of failure.
CDF of EP based on measurements and simulated results from S1 and S2 without external parameters compared to FM. The horizontal axis shows the EP in kWh·m^{-2}·a^{-1}.

Table 7. Probability of failure from the predictive models and field measurements.
The impact on the probability of failure from the chosen design criteria level for the datasets field measurements (FM), S1, S2, and S2 excluding fixed parameters.

Design Criteria [kWh·m^{-2}·a^{-1}]	FM	S1	S2	S2_Excl
65	20%	99%	68%	9%
70	10%	89%	37%	2%
75	4%	60%	13%	0%
80	1%	23%	3%	0%
85	0%	4%	0%	0%
90	0%	0%	0%	0%

4.3.1.4 Influence on the Accuracy

As described in section *1.1 Background*, there is a difference in the input models and results between sensitivity and uncertainty analyses. The study presented in *Paper II* shows the difference in approach when using an uncertainty analysis, where the results indicated that a more significant variation in the input model resulted in a more accurate result. Contradictory to the approach in a sensitivity analysis where a significant variation in the output indicates which input parameter to alter and improve. However, since the uncertainties in the real world are significant, as shown by the variation in actual EP, the input data must be similarly uncertain.

4.3.2 Design Optimisation and Stakeholder Perspectives

This step uses only the single-family case building. However, future studies could apply the method to other types of buildings. The results in Paper III using the developed method was presented in steps, starting with the probability of failure for the two design options, thus adding a design compared to Paper VIII, followed by defining three stakeholders and quantifying the consequence for each. Different consequence models were used to showcase the method's adaptability. First, using the EPC model for the building contractor. Second, using the LCC model for the property developer and private building owner with different input data.

There were two categories of uncertainties required to quantify for the risk analysis, probability and consequence. In the first step, using the described method and the BPS results for the two design options (DOA and DOB) and the design criteria based on the Swedish passive house criteria, the probability of failure was quantified, followed by quantifying the consequence of failure using the two consequence models and three stakeholders to quantify the influence on the results. Finally, the results from the simulations presented above are converted into CDFs to quantify the probability and consequence of failure to enable risk analysis.

Two design options were defined and used as examples to showcase the PRA method. The design options included a difference in the performance of the external walls and windows. All other parameters were kept identical in the two design options. However, both design options, unless otherwise specified, included the same uncertainties. The stochastic parameters were assigned the same variance and shape as in the previous studies. The two design options – A and B - evaluated in the comparative study were the alternative design with the different windows and modified external wall performance; see design options in Table 8. The cost per unit (m^2) for the design options was estimated using a cost calculation database frequently used in Sweden: Wikells Sektionsdata [71].

Table 8. The difference in properties of the two design options – DOA and DOB
Presents the differences between the design options used as examples in the risk analysis, including the design value for the parameter performance, acquisition cost per m², and the external walls' construction.

Parameter		Unit	Design Option A (DOA)	Design Option B (DOB)
Windows	Thermal transmittance	$W \cdot m^{-2} \cdot K^{-1}$	0.9: T [0.7, 0.9, 1.1]	1.1: T [0.9, 1.1, 1.3]
	Cost	SEK per m² [71]	5 496	4 361
External walls* (mineral wool and wood/steel studs)*	Thermal transmittance	$W \cdot m^{-2} \cdot K^{-1}$	0.13	0.18
	Construction – insulation layer thickness, inside-to-outside	mm	70 + 195 + 80	45 + 120 + 80
	Cost	SEK per m² [71]	2 346	2 210

** Performance is dependent on the variance in mineral wool properties.*

4.3.2.1 *Probability of Failure*

The uncertainties impacting buildings' EP were included in the BPS to quantify the probability of failure in attaining the EP criteria for the two design options. Figure 17 illustrates the difference in results between the design options A and B regarding the probability of failure presented as CDF.

The CDF was used to calculate the probability of failure – exceeding 60 kWh·m^{-2}·a^{-1} – for each design option. Calculating the probability of failure resulted in a probability of failure of 7.6 per cent for design option A and 32.1 per cent for design option B. Using the different consequence models, the calculations to quantify consequences for the stakeholders use the quantified variation in EP from the simulations as input data.

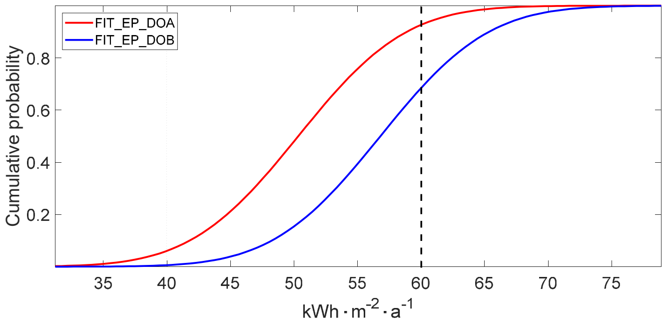


Figure 17. Probability of failure quantified using CDF plot.
The CDF plot for DOA (n=998), indicating a probability of failure of 7.6 per cent, and DOB (n=997), with a probability of failure of 32.1 per cent, using the design criteria (dashed line) and based on the results from the BPS imported and analysed in MATLAB.

4.3.2.2 *EPC - The Building Contractor*

A risk level was calculated for each DO, using the quantified probability of failure and consequences. Table 9 presents a summary of the results. To visualise the results and facilitate the decision process, Figure 18 illustrates the results of the study. Using the results for one building, a conversion to account for the whole project of 26 houses was performed, resulting in a total liability for DOA of € 20 400 and DOB of € 31 200.

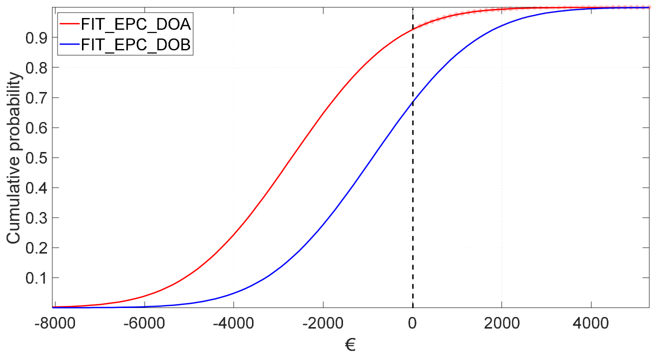


Figure 18. The consequence of failure for the building contractor.
The CFD plot is based on the EPC model and one building. The vertical dashed line illustrates the point where the building contractor incurs liabilities. Calculating the total liability for DOA and DOB uses the surface area between the curves and this line (n=995).

Table 9. Results using the PRA for the building contractor.
Results from quantifying the probability and consequences of failure for the DO from a building contractor viewpoint using EPC.

Performance indicators	Design Option A	Design Option B	Δ
Probability of failure	7.6 %	32.1 %	+24.5%
Consequences	€ 20 400	€ 31 200	- € 10 800
Acquisition cost	€ 1 135 700	€ 1 025 300	€ 110 400

The increase in acquisition cost for choosing DOA over DOB is about ten times higher than the increased cost in liabilities for choosing the cheaper alternative (DOB). However, in the example above, if this analysis is performed early in the building process, the building contractor may need the high performing option to fulfil the design criteria. If the quantified levels are deemed as an acceptable risk level, it is often possible for the building contractors to pass on parts or most of the increased acquisition cost from a higher-performing option to the building developer.

4.3.2.3 LCC - Property Developer and Private Building Owner

The results from the LCC analysis - for the calculation periods 30, 40, 50, and 60 years - are presented as a CDF with relative values; negative values indicate that option DOB is the preferred DO from a financial perspective, while positive values indicate that DOA is the financially preferred option. Figure 19 presents the results for the property developer, with a discount rate of 5 per cent, and the private building owner, based on an average 10-year interest rate resulting in a discount rate of -0.59 per cent, in Figure 20 a summary of the probability of DOA being the financially preferred option (Table 10). The results show that DOB is the most financially preferred option for all calculation periods for the property developer, although this option significantly increases the probability of not attaining the EP design criteria.

On the other hand, the results show that DOA is the most financially viable option for the private building owner for more extended calculation periods, and with a lower interest rate, this trend improves. As expected, the example with a 60 years calculation period results in the most significant shift towards the more energy-efficient design.

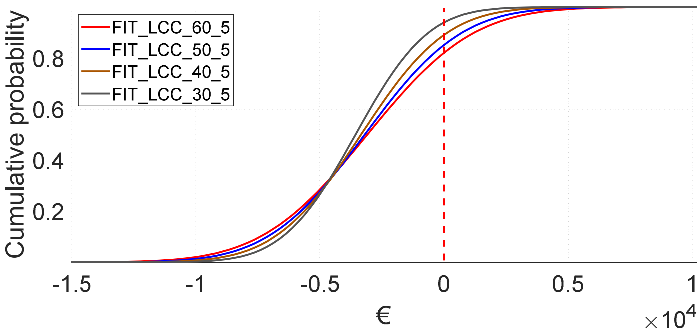


Figure 19. Results from the LCC analysis for the property developer.
Presents the CDF plot for the results from the LCC calculations for the property developer, with a discount rate of 5 per cent, with one curve for each calculation period of 30, 40, 50, and 60 years (n=995). The vertical dashed line illustrates the point where the outcome of DOB being the financially viable option (negative values) to DOA (positive values).

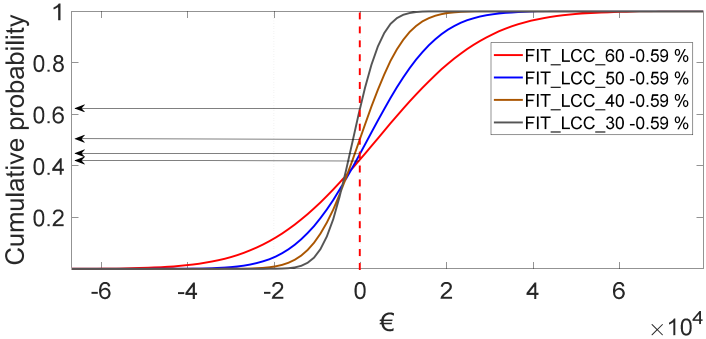


Figure 20. Results from the LCC analysis for the private building owner.
The CDF *plot* for the results from the LCC calculations for the private building owner, with a discount rate of -0.59 per cent for the calculation periods 30, 40, 50, and 60 years (n=995).

Table 10. Results using the PRA for the property developer and private building owner.
Results from the cost analysis using LCC, the percentage indicates the probability of DOA being the financially better option.

Lifecycle [years]	30	40	50	60
Property developer	6 %	11 %	15 %	18 %
Private building owner	37 %	49 %	55 %	57 %

4.3.2.4 Risk Analysis

The examples presented above originate from the same problem or question;

> Which option to choose and why?

However, the answer depends on the stakeholder perspective. Using the concept of risk, the probability of failure for each option remains constant for all evaluated stakeholder perspectives. Nevertheless, the answer is stakeholder dependent because of the difference in consequences, and consequently, risk.

For the building contractor, there is a significantly increased risk when choosing option B. However, because the cost of choosing option A is also much higher, the decision is complex and depends on the subjective acceptable risk level of the building contractor. If done early in the building process, an aspect that could influence the decision is if parts of the increased investment cost could be passed on to the property developer through an increased bid price during the tender process. Either by including the total investment cost; alternatively, the risk cost could be included and used to alleviate the costs incurred if the unwanted event occurs. Both alternatives would reduce the risk in the project for the building contractors.

For the property developer, the results indicate that choosing option B is the financially beneficial option with the used boundary conditions of this study. Adding other conditions could alter the outcome.

For the private building owner, who, in the example, has a lower required rate of return on the investment, the results reverse for most time frames.

Thus, the outcomes of the PRA, depending on the stakeholder, results in the answers: yes, no, and maybe. Which, from a demonstration point of view, was a successful result. One possible outcome that these examples did not include was if the risk is so high that the answer is not to participate in the project. However, more extreme options would be needed for the PRA to result in that option.

There is also a balancing act between reducing the risk of not attaining a design criterion and increased acquisition cost from higher-performing design options.

The results are positive from the entrepreneur's perspective since the actual EP was much better than calculated; however, an optimised building design could achieve the desired performance at a lower cost. This discrepancy could affect an entrepreneur's chances of winning a bid if the bid is too high due to the building's design being better than required. Thus, further investigation and quantification of uncertainties for design decided parameters are needed. Similarly, there is a balancing act from the point of view of CO_2 emissions and LCA. A future expansion of the method could include these objectives.

The results of the studies presented in *Papers II, III, and VIII* follow Kaplan and Garrick's suggestion of presenting the risk relative to the cost and benefit of the options presented in section *2.1 Risk, Probability, and Consequence – What is it?*

The developed method follows the principles from ISO 31000, as presented in section *2.1 Risk, Probability, and Consequence – What is it?*. Although not yet integrated, the method provides a structured and comprehensive process for quantifying risk in a customisable way showing different applications and implementing different models, using examples of different stakeholders to showcase the inclusiveness of the method. The developed method also shows how to include uncertainties dynamically to quantify the effect on the risk, quantified based on best available data, examples of different human and cultural factors, and how this could continually be improved when new data is available.

4.4 Analysis of Data, Processes and Results not included in Papers

The published papers do not include all performed investigations, analyses, and results, either because of limitations in space, lack of time, or relevancy. These investigations, analyses, and results are instead presented, put into context, and discussed below.

4.4.1 Level of Detail

Predicting the EP using BPS and an abstracted computer model of a building to represent the building characteristics and real-world operation requires balancing factors such as aim, design criteria, time- and cost constraints. One aspect of the balancing act is the granularity for the data resolution for the input models and the computer model of the building, the spatial and temporal resolution, and the impact on the robustness of the output. Changing the resolution for one of the factors impacts the others. How this study accounted for these perspectives are described below.

4.4.1.1 Input Model Resolution

This study uses two options for the input model resolution for parameters. The options were to assign the input model on a *global level* - with one sampled value for the whole building model - or to a *local level*, with one sampled value for each building model zone. The chosen level of detail and model type determines how to decide on the input data resolution.

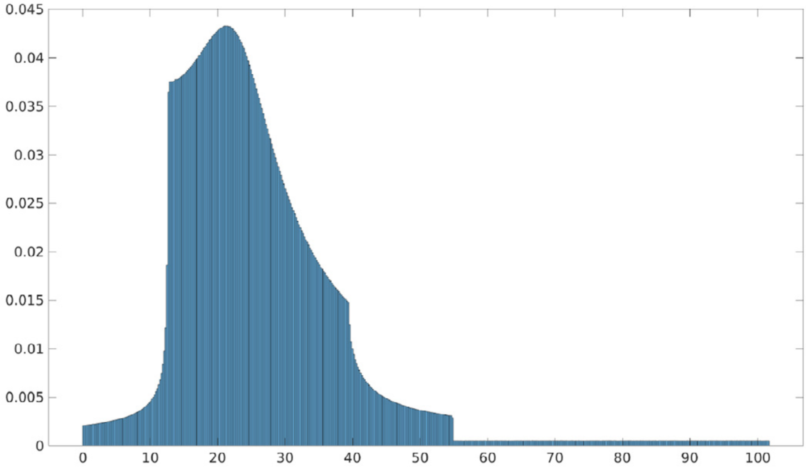


Figure 21. Household electricity model for the local level.
An example of PDF for the household electricity at a local level was found in Westin [81] and implemented in this study's case building. The unit on the horizontal axis is kWh·m^{-2}·a^{-1}.

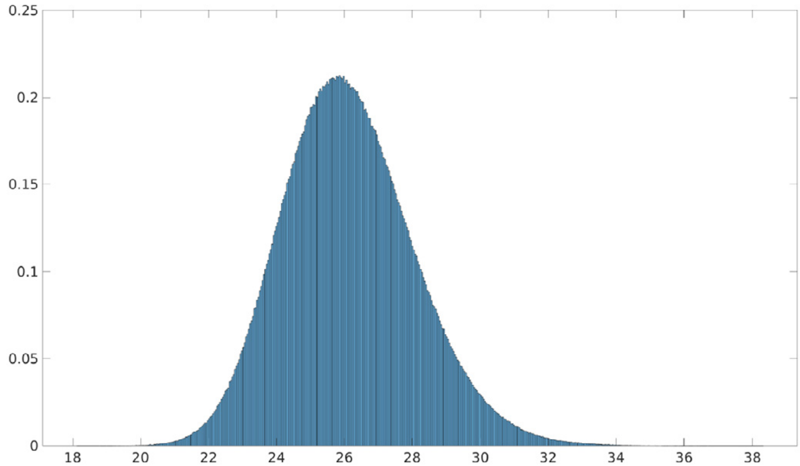


Figure 22. Aggregated household electricity using case building and model
The household electricity - at an aggregated level - for the case study building when sampled using the PDF in fig. 16 on a local level. The unit on the horizontal axis is kWh·m^{-2}·a^{-1}.

The study presented in *Paper II* shows an example of how the level of detail in the building model resolution affects the input model resolution, using household electricity as the example. The example shows how the input model resolutions of the input data model for household electricity influence the EP of the building. The example uses two input models for household electricity, the standardised model used for benchmarking in the Swedish building regulations and a new model based on empirical data from residential buildings. The standardised value in Sweden for household electricity is 30 kWh per m² and year, according to BEN2 [24]. Westin et al. [81] defined a household electricity model at the local level based on empirical data from 3000 apartments in residential buildings. Figure 21 presents an example of sampled values at the local level using this model. Shown in Figure 22 is the case building's aggregated household electricity from using the model on the local level in all 1000 simulations. The differences in shape and variation between these figures showcase the importance of using the correct model on the correct level.

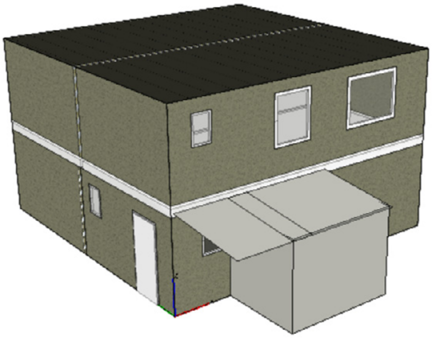
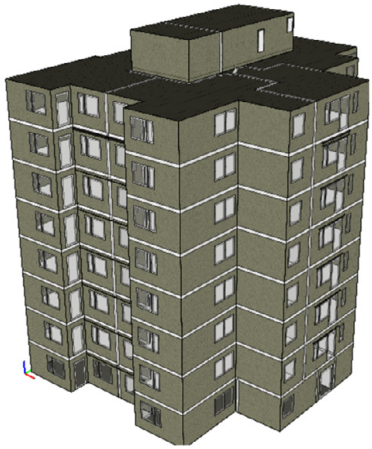
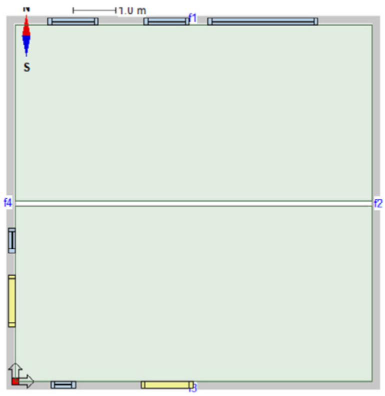
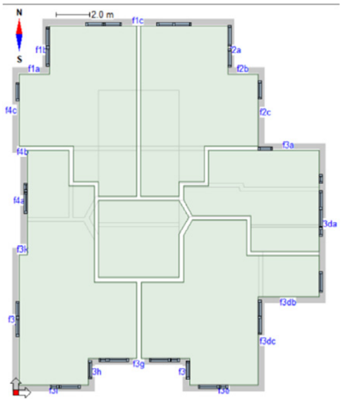
4.4.1.2 Zones - Spatial Resolution

The boundary conditions of a project determine the resolution to use. For example, a computer model of the building requires abstracting the building and dividing it into zones based on the use of the space. These zones could be on the whole building level (single-zone model) or divided into smaller zones (multi-zone model), with alternatives such as the whole floor plan, whole apartments, or rooms. Each zone requires input data relevant for the modelled space and a schedule for the usage of the zone.

The first step was to identify how and to what effect an increased spatial resolution could showcase. The identified factors included increasing the building's scale, the complexity of the building systems, and modelling the impact from the occupant variability, thereby adding additional quantified uncertain parameters affecting the EP that could increase the accuracy of the predictive model and reduce the performance gap.

A logical continuation to increase the spatial resolution from the previous study (*Paper VIII*) – using a single-family house – was to use a multi-family house (*Paper II*). The multi-family house includes multiple apartments with different occupants, enabling a solution to increase the building model's spatial resolution by increasing the number of zones. Although both models can use temporal variability, introducing multiple zones with variability in input data introduces new effects from using temporal variability. In addition, an increased level of detail increases the flexibility in the types and sources of uncertainty modelled. One effect of the increased level of detail is that it is possible to choose either the local or global level to use as a source of uncertainty. Presented in Table 11 is a comparison between the two case buildings showcasing the differences.

Table 11. Comparing case buildings.
Shows an overview of the two case study buildings in phase two and the differences in typology, building models, number of zones, HVAC system, and size of the buildings.

Case building	Phase 2, Single-family house	Phase 2, Multi-family house
Building model	 [77]	
Floor plan		
Number of zones	4	52
Number of floors	2	8
Types of zones	1 type, residential	Seven types, two main categories: Residential – 2 Room & Kitchen, 3 Room & Kitchen; Non-residential – Bicycle storage room, Laundry room, Storage room, Mechanical room, Staircase
Floor area, m²	143	2570
Heating system	District heating	District heating
Ventilation	Central AHU with heat recovery	Central AHU with heat recovery

There was a need for increasing the granularity of the model to enable the use of unbalanced airflows and model the wind-driven infiltration. A consequence of this was that the number of zones increased from 4 to 52, the types of zones from one (residential) to a total of two types of residential zones and five types of non-residential zones. The main difference between the residential and non-residential zones was the supply and return airflows. The increased number and types of zones introduced new possibilities for modelling the influential factors affecting EP. The first step was to determine which level to use a source of uncertainty on, either the local or global. The next step was to increase the number of parameters and implement new types and sources of uncertainties. Depending on how to model these, new probability density functions may be needed. Dependencies between parameters when defining variance and sampling input data may also be needed when changing the type of uncertainty.

4.4.1.3 Schedules – Temporal Resolution

The model for including the temporal resolution in the computer model was by using schedules (also referenced as profiles). The schedules are used as models for the usage variability of a space or function, i.e. if an occupant was present or the lights were on. The use of schedules is a common simplification to model the temporal resolution of parameters in BPS.

However, there are more advanced models for including the temporal and spatial variability of parameters in BPS. The advanced models include temporal and spatial variability by imitating how occupants move through space, i.e. rooms, over time and perform tasks that result in internal heat gains. One approach to improve the accuracy of the PRA method can be to investigate how to implement and test the probabilistic approach for occupant behaviour. Either by sampling from a database of profiles created based on field measurements, similar to the method for household electricity developed by Fransson et al. [83] or using methods and models developed in IEA Annex 66. The studies of Annex 66 focused on creating stochastic models regarding the occupants' activity from which to sample input data. This approach is similar to the method developed focusing on the opening of windows and control of thermostats by D'Oca et al. [84]. IEA Annex 66 defines occupant behaviour and divides the influence of occupants into the factors; occupant movement, presence, and action. As part of the project was the development of a modelling tool for occupant behaviour. However, as mentioned in Annex 66, page iv:

> "Choice of occupant behavior simulation models depends on the building context. Studies suggest that stochastic models, to capture spatial, temporal, and individual diversity, do not necessarily always perform better than simplified deterministic models."

Thus, the first step was to identify how and to what effect an increased temporal resolution could showcase. The identified factors of this study included the occupant presence, variability of usage in DHW and household electricity, seasonal variability in evaporation of built-in moisture, and activation of functions in domestic hot water circulation, kitchen ventilation, and airing. The increased temporal variability adds additional variability in the energy balance and changing the effect from uncertain parameters affecting the EP in an increasingly realistic model that could increase the accuracy of the predictive model and reduce the performance gap.

Although still highly simplified, the continued work focused on how to increase the level of detail for the schedules. For S2, the aim was to create a more detailed profile of the temporal variability using compiled data to better imitate the buildings' real-world operation. Paper II's parameters differ between S1 and S2 and required specific schedules and granularity, as presented in Table 12.

The profile's granularity/resolution and shape depend on the real-world events that the models aim to imitate. Therefore, this evaluation differs between the two evaluated cases (S1 and S2), where S1 uses standardized input data and profiles with no temporal variability and S2 aims to imitate the building during a real-world operation in more detail and thus includes profiles with temporal variability. For some parameters, there are hourly, weekly, and monthly variations over the simulated period.

Table 12. Overview of schedules and sources.
The granularity of the profile for parameters.

	Schedule			Source		
Parameter	**Hourly**	**Weekly**	**Monthly**	**Hourly**	**Weekly**	**Monthly**
Occupant presence – heat gain	x	x	-	[85]	[82]	-
Domestic hot water	x	-	x	[85]	-	[86]
Plug load / Household electricity	x	x	x	[81]	[81], [82]	[81]
Built-in moisture	-	-	x	-	-	*
Domestic hot water circulation	-	-	x	-	-	*
Kitchen ventilation	-	-	x	-	-	*
Airing (opening of windows)	-	-	x	-	-	*

*Estimated based on the heating season.

For some parameters, a simplification of an annual variability was deemed enough, as with the DHW included in the simulation as an external parameter not impacting the dynamic simulation of the EP. On the other hand, for household electricity, the profile was divided into three levels: daily (Figure 23), weekly (Figure 24), and annual variation (Figure 25). Since there is data available to base the profiles on, the parameter is included dynamically in the simulation.

For external parameters, the sampled values from the PDF of the parameter determines the total annual energy use of these parameters, and thus the profiles should not impact the sum.

If the analysis focused on the annual total energy use, a profile for these parameters would have been unnecessary. However, this study's analysis aims to increase the granularity of the output and analyse the congruence of the simulated output with the measured performance on a minimum monthly basis.

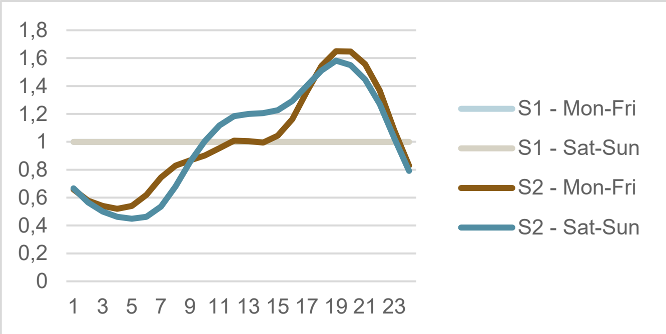


Figure 23. Household electricity – Daily profile
Shows the profiles for S1 and S2 with a daily variation and the factor used for each hour of the day.

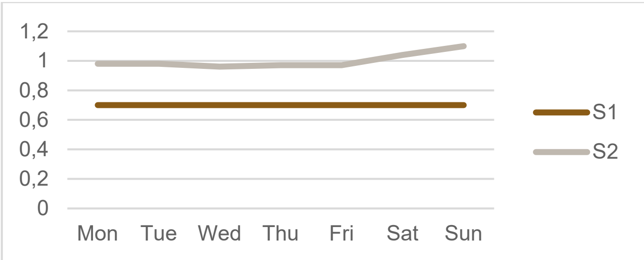


Figure 24. Household electricity – Weekly profile
Shows the profiles for S1 and S2 with a weekly variation and the factor used for each day of the week.

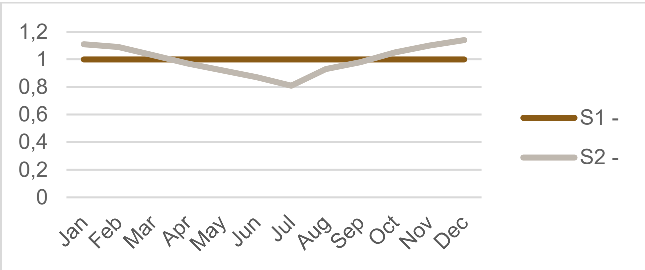


Figure 25. Household electricity – Seasonal profile.
Presents the household electricity profiles used in S1 and S2 with a seasonal variation and the factor used for each month of the year.

Based on the heating season - Several of the profiles are dependent on the heating season of the buildings; based on the BPS for the building, the heating season is estimated and simplified from the beginning of October to the end of April. Thus, accounting for the difference for some parameters occurring during and outside the heating season results in two opposing profiles. The probabilistic parameter losses of *built-in moisture, kitchen ventilation losses,* and *airing losses* uses *during the heating season* profile (Figure 26). The probabilistic parameter *domestic hot water circulation losses* use the *outside heating season* profile (Figure 27).

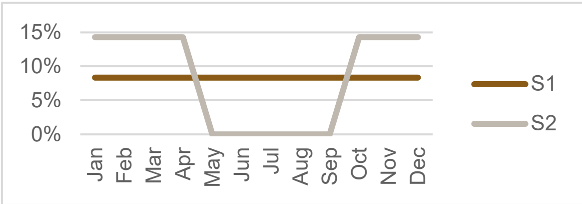


Figure 26. During the heating season.
Graphs show the profile for the distribution for S1 and S2 during one year.

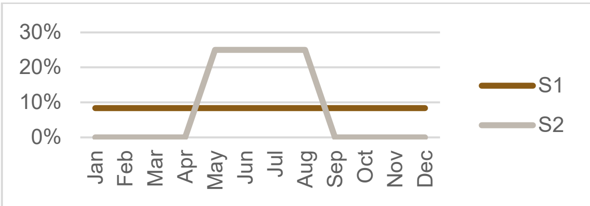


Figure 27. Outside heating season.
Graphs show the profile for the distribution for S1 and S2 during one year.

4.4.2 Analysis of Data from Field Measurements

The data collected from the objects used in the study presented in *Paper II* consisted of both the results from the deterministic simulations from each project and the data from field measurements. The data consisted of space heating, DHW, and electricity for building services. The data verification and validation process reduced the number of objects to 28. However, the data needed additional processing before being used in this study. Both the field measurements and the deterministic simulation results follow the practice set by the Swedish building regulation.

The data enabled a more detailed analysis of the accuracy of the deterministic simulations, using the deterministic simulations from each project as a population of predicted outcomes, compared to the field measurements.

An initial analysis of the data for the three categories identified the following possible analysis.

The regulation determines a set value for DHW when predicting the EP of buildings using deterministic simulations. Thus, for DHW, there were no deterministic predictions to analyse and compare to the actual outcome.

The objects energy use for space heating is affected by the climate. Therefore, comparing the data pairwise – using the corresponding deterministic simulation and field measurement from an object – does not distinguish between predicted and actual EP because of the effect of climate. However, when using all objects as a population of identical buildings and comparing the field measurements against predictions from probabilistic simulations using only one location, the climates of the different locations introduce an error. Thus, for the probabilistic method, there is a need to adjust the effect on energy use for space heating from differences in climate between the measured and simulated objects to enable the validation process of comparing distributions for predicted and actual EP. Consequently, the identification and evaluation of a normalisation process for the space heating were needed. Presented below are the results from the evaluation of the used normalisation process.

Contrary to space heating, the electricity for building services has a limited effect on the climate, and thus the comparison is made without processing the measurement data. Presented below is an analysis of the accuracy of the predicted and actual outcomes.

4.4.2.1 Analysis of The Normalisation Process for Space Heating

A normalisation process is required to reduce the effect from different locations on the space heating demand before comparing predicted and actual EP. Searching for solutions for compensating for this effect identifies a normalisation process using geographical location factors described in BBR. Before choosing this solution, an evaluation compares the deterministic simulations and field measurements before and after the process is applied to determine the normalisation method's effectiveness. The evaluation compares the space heating before and after applying the correction to the field measurements and the results from deterministic simulations performed for each object since those used the actual geographical location and climate. The analysis also evaluated if there was a difference in effectiveness if applied to simulated or measured data.

Unfortunately, the dataset is too limited to draw definitive conclusions. Therefore, the analysis uses the 28 objects presented in *Paper II*. In addition, a control test was performed with all 52 objects with data to determine if any significant deviations were present. The results are presented below in Figure 28, Figure 29, Figure 30, and Figure 31. The data indicates that the correction of the normalisation process reduces the effect of the geographical locations and differences in climate. However, the precision of the correction using the geographical location factors is better for simulated data than measured data; however, the variation in climate boundary conditions is reduced significantly for both.

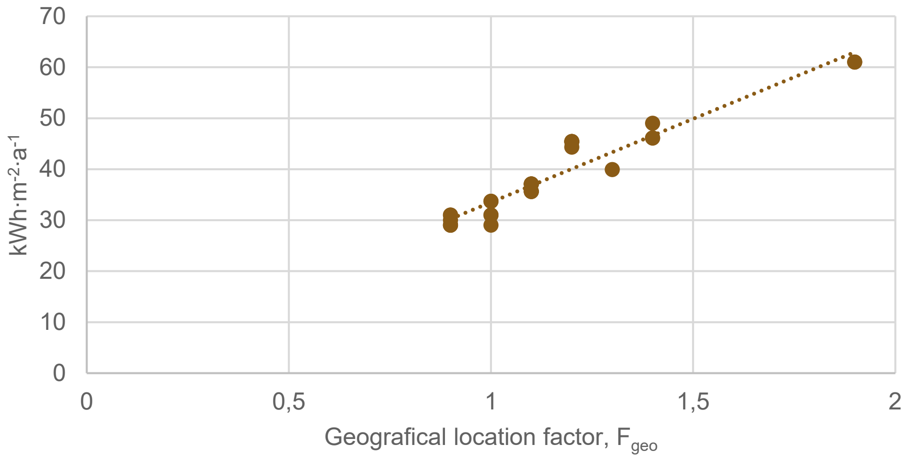


Figure 28. Deterministic simulations - Correlation between energy use for space heating and geographical location factor before correction.
Presents the simulated results using the deterministic method for the objects for space heating demand, in $kWh \cdot m^{-2} \cdot a^{-1}$ on the vertical axis, in buildings before correction based on the geographical location factor on the horizontal axis (n=28).

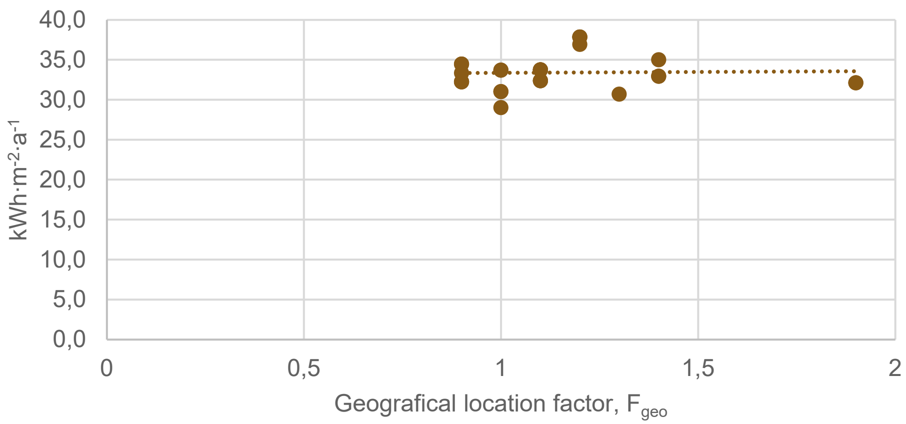


Figure 29. Deterministic simulations - Correlation between energy use for space heating and geographical location factor after correction.
Presents the simulated results using the deterministic method for the objects for space heating demand, in $kWh \cdot m^{-2} \cdot a^{-1}$ on the vertical axis, in buildings after correction based on the geographical location factor on the horizontal axis (n=28).

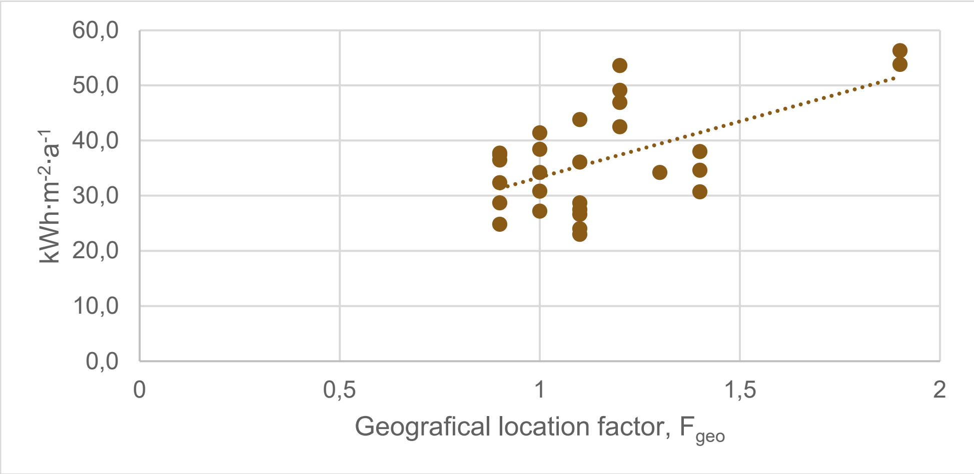


Figure 30. Field measurements - Correlation between energy use for space heating and geographical location factor before correction.
Field measurements from objects for space heating, in $kWh \cdot m^{-2} \cdot a^{-1}$ on the vertical axis, in buildings before correction based on the geographical location factor on the horizontal axis (n=28).

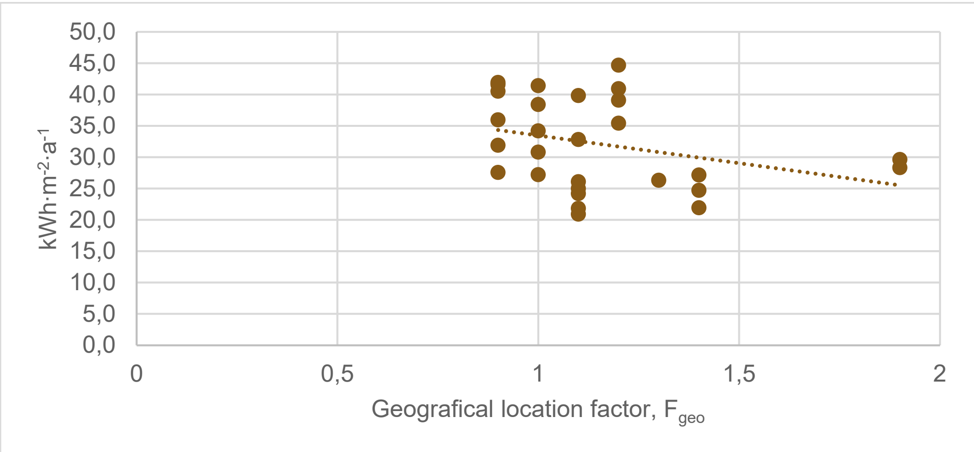


Figure 31. Field measurements - Correlation between energy use for space heating and geographical location factor after correction.
Field measurements from objects for space heating, in $kWh \cdot m^{-2} \cdot a^{-1}$ on the vertical axis, in buildings after correction based on the geographical location factor on the horizontal axis (n=28).

4.4.2.2 *Analysis of Data from Electricity for Building Service*

Comparing the results from the deterministic simulations to field measurements using the compiled data from the objects enables evaluating the accuracy of the predicted electricity for building services. The initial comparison shows a good agreement in variation between the two data sets by the histograms, as shown in Figure 32.

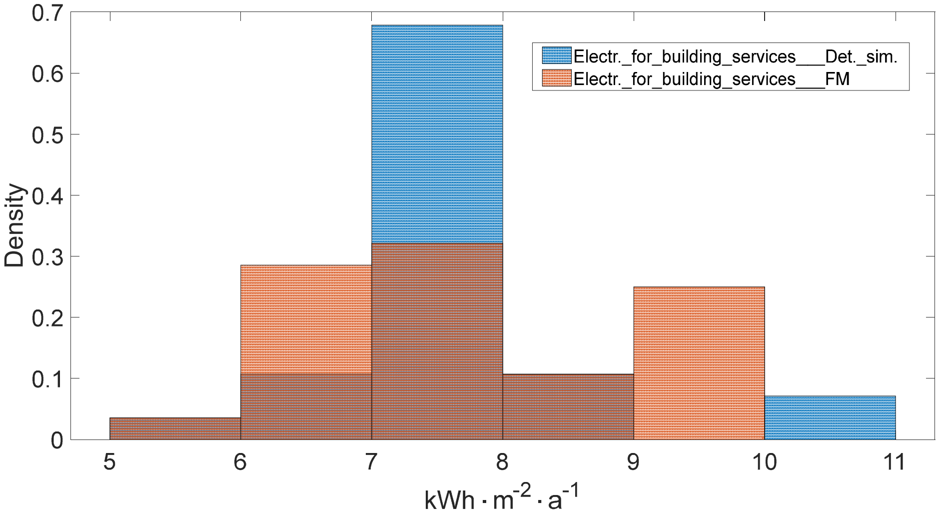


Figure 32. Data showing predicted and actual energy use for electricity for building services in the objects.
Histograms showing predicted, using deterministic simulations, and actual electricity for building services based on field measurements in same objects (n=28). The third colour is where the distributions overlap.

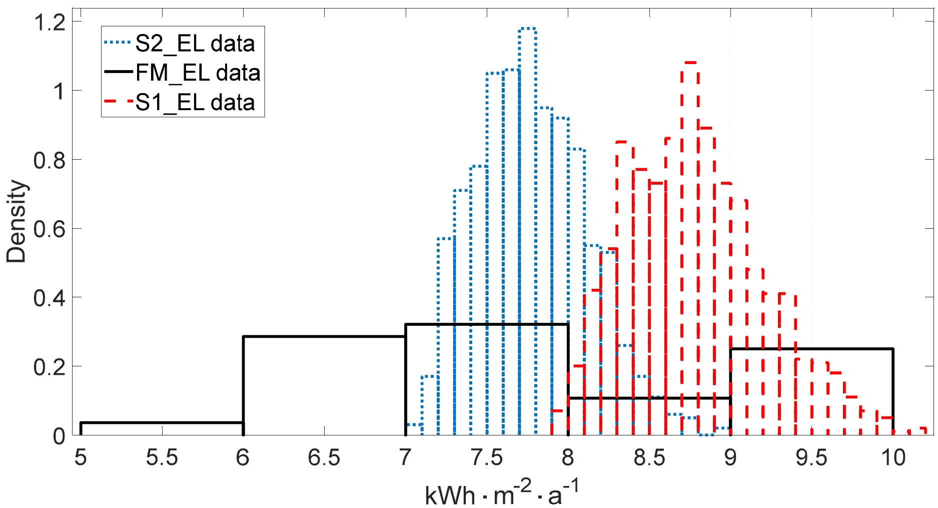


Figure 33. Probabilistic simulation results from Paper II.
Density plot of electricity for building services based on FM and simulated results from S1 and S2.

The variations shown in Figure 32 show a higher accuracy between the deterministic variation and actual outcome than that from the probabilistic simulations presented in *Paper II, see* Figure 33. However, using a scatter plot and linear regression to compare the deterministic predictions and outcomes for specific objects gives a different result, with a low correlation between predictions and actual performance (see Figure 34).

Although some modellers have interpreted the conditions and estimated input data giving results comparable to the outcome measured in field measurements, there seems to be a low correlation between predicted and actual outcomes. The data showcases the importance of using a probabilistic approach when making predictions and, in *future work*, identifying which parameters were quantified differently and using what data or assumptions to improve the accuracy of the probabilistic model.

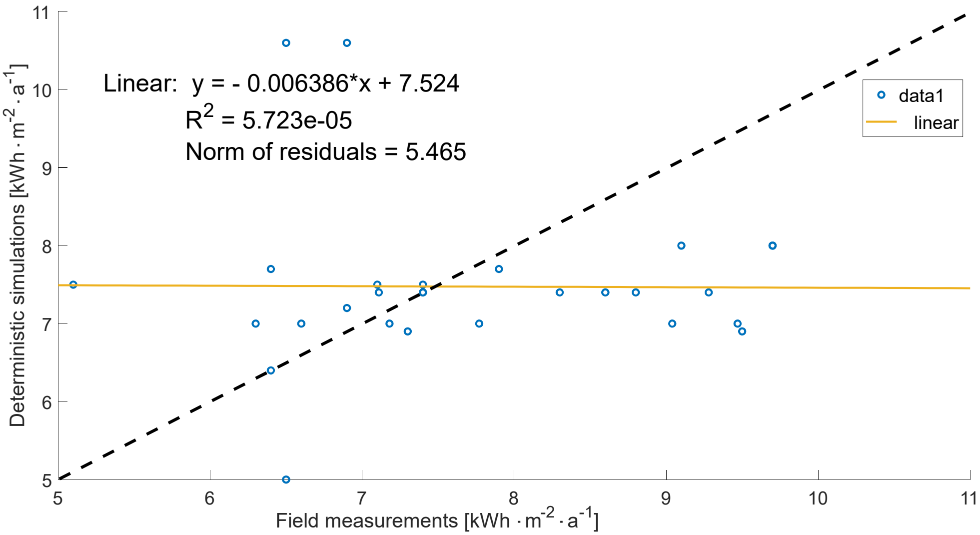


Figure 34. Correlation between predicted and actual use for electricity for building services per object. Scatter plot showing electricity for building services, comparing predicted using deterministic simulations against field measurements and a linear regression model to indicate the correlation (n=28). The dashed line would illustrate the expected linear regression model if the deterministic simulation results were accurate.

4.4.3 Energy Performance Gap

The performance gap, as previously defined, is often seen based on a single object, comparing the predicted EP to the actual EP, exemplified using object six from Paper II in Figure 35. Thus, when using a deterministic approach and calibrating the input data for the BPS model, a simplification is to conceptualise the problem in one dimension. Depending on if a parameter has a positive or negative correlation with the EP, the parameter's value is correspondingly increased or decreased, resulting in a shift in that single value for EP to reduce the performance gap. However, it is essential to differentiate between the type of calibration that only arbitrary changes input data to achieve the desired result or based on actual changes in the actual building design then included in the model's input. Furthermore, calibrating a model based on measured data is problematic since, without detailed measurements of the phenomena modelled, there could be other causes resulting in the same outcome.

If applying the approach to a population of identical buildings instead of a single building, the performance gap from each building in the population could be seen as an observation of the possible outcome for the specific building design, as exemplified using the 28 objects from Paper II in Figure 36. Using this data and presenting the relative values, i.e. the performance gap, results in a distribution of values, as shown in Figure 37. Thus, a process with multiple simulations is needed to predict EP as a distribution to reduce the performance gap. Furthermore, the energy performance gap is a multi-dimensional problem to solve when calibrating the model. Therefore, it is impossible to manipulate the input data in one dimension to either increase or decrease the predicted EP, resulting in a reduced performance gap.

Identifying this multi-dimensional problem was one of the results of *Paper II* and the conceptually contradictory finding that a reduced accuracy in input data – i.e. a more significant variation for the distribution - increased the accuracy in predicting the performance gap by reducing the difference between the response in predicted EP compared to the actual EP.

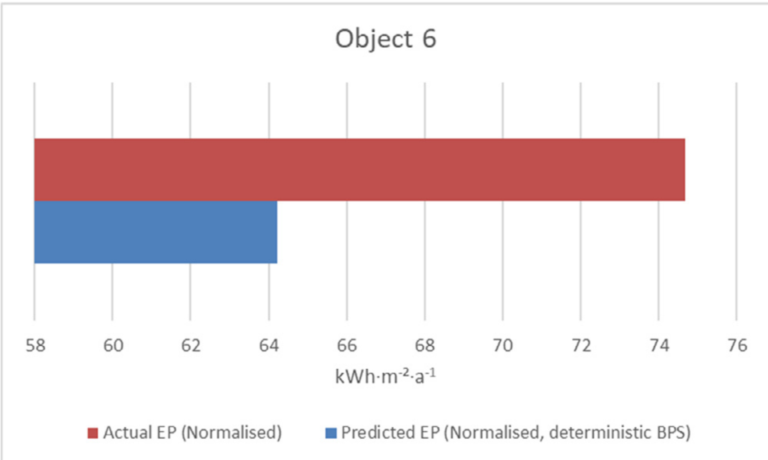


Figure 35. Energy performance gap, single object.
Example of the energy performance gap, i.e. the difference between the predicted EP and the actual EP.

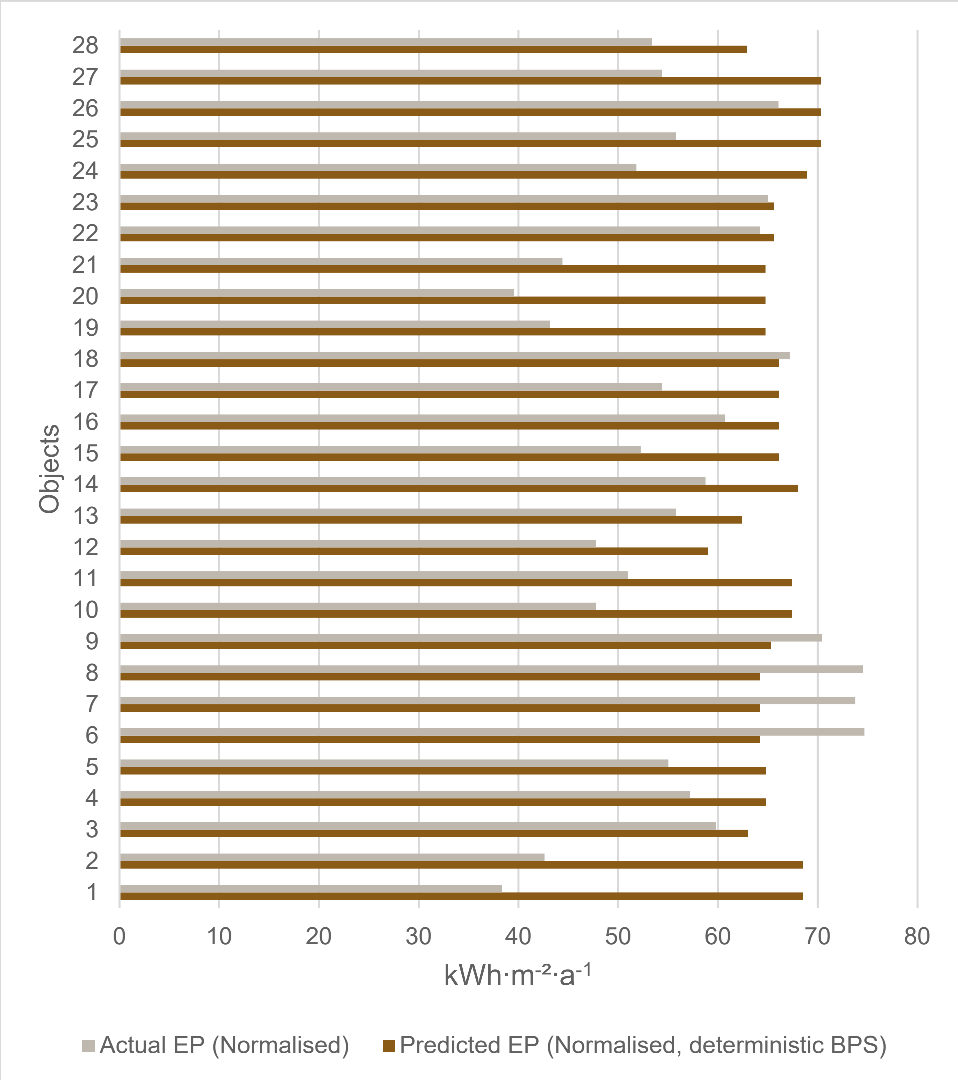


Figure 36. Energy performance gap, multiple objects.
Predicted EP using a deterministic approach and actual EP for all 28 objects from Paper II.

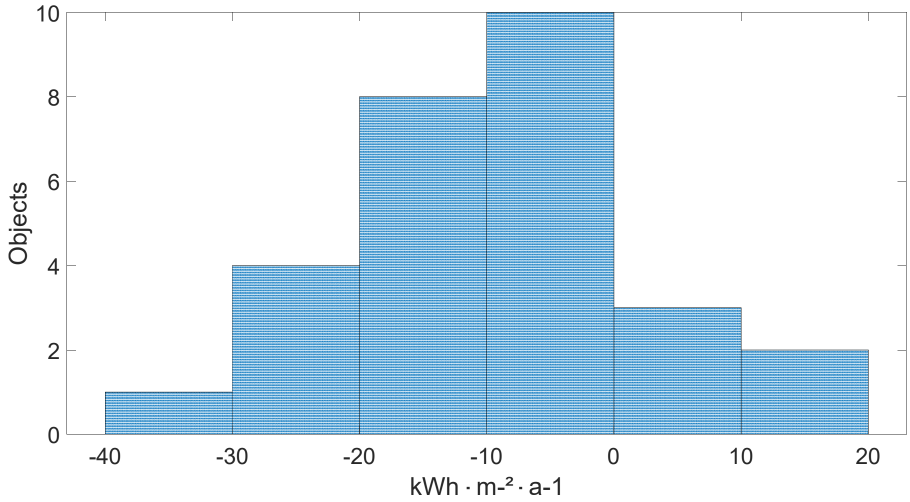


Figure 37. Quantified energy performance gap of multiple buildings.
Histogram showing the energy performance gap quantified by the difference between predicted EP using a deterministic approach and actual EP.

4.5 Relevance for the Building Industry

The outcomes of investigating the probabilistic approach have shown if and when it could be used (*Paper VII*), how to implement and use it in the building design process (*Paper III and VIII*), how to use the results for informed design decisions (*Paper III*), the reliability of the results and how to improve it (*Paper II*), and examples of who and how to use it (*Paper III*).

What is known is that the performance gap erodes confidence/credibility in the engineering sector. However, it might be easy to suggest that the performance gap's cause is a mismatch between designer and energy modeller, design and construction or designed operation and use compared to how the building is used and operated in the real world. The building developer expects the building design suggested by the building contractor to fulfil the design criteria for EP as predicted by the BPS during the design phase. If not attaining a design criterion during the operational phase, the stakeholders' confidence in the contractor is eroded for future projects.

Similarly, the public confidence in that the building sector will attain the increased energy efficiency and reduced carbon emissions that the future building code dictates and required to achieve the set goal for a carbon-neutral future. Therefore, eliminating or reducing the performance gap is essential to further reducing the building stock's energy demand while also improving the engineering sector's credibility. Furthermore, as shown in the sections above, using the probabilistic approach should reduce or at least result in a better understanding of the performance gap and why it occurs.

Although the current version of the method only focuses on the energy performance of buildings, the optimisation of a building design must also fulfil other requirements for a healthy building environment that are outside the scope of this study, i.e. daylight and thermal comfort.

4.5.1 Impact on Stakeholders

Implementing the results and method developed in this research project would impact many stakeholders, i.e. building designers and engineers, as exemplified in *Paper III*. However, other stakeholders not included in Paper III could likely benefit from the results and outcomes of this project also, i.e.:

- For a broad implementation of the probabilistic method to occur, it likely requires policymakers to include the method in the building regulation. In Sweden, developing the building regulations is the Swedish National Board of Housing, Building and Planning's responsibility. If implementing the method, the likelihood of regulation fulfilment in newly constructed buildings will be improved. In addition to the building regulation, the Swedish Energy Agency also aims to reduce the total energy use in Sweden, which should be aided by improved accuracy in predictions.
- Implementing the probabilistic method in the building code is a solution to improve the accuracy of the calculated energy use in buildings. The outcome of the probabilistic method shows the potential to achieve lower energy use in buildings and help the goal of reducing the overall energy use in buildings. One way of attaining this is by reducing the uncertainties in the design phase, defining a more accurate failure level, and clarifying the consequences a failure entail.
- The building sector will be impacted differently, depending on the roles and contracts involved, as is shown by the stakeholders in the study presented in *Paper III*. One possible change to the Swedish building sector would be for the developer to require the building contractor to operate the building for a set amount of time, e.g. 20 years, similar to a tested method for roads and road service in Sweden. The long-term approach should increase the building contractor's incentives to take the life-cycle cost of a decision into account when designing a building.
- The building energy modellers and energy consulting companies could use the results of this project to gain insights into how to apply the probabilistic method and model the input parameters to increase the accuracy of their models and results, as discussed in Paper II and III. The results showed

examples of how to identify, quantify, and model parameters. In addition, the results showed that the focus should be on quantifying the actual variation, not reducing the variation to provide an apparent accurate result compared to real-world objects showed using field measurements.

- The energy software developers, the two software developers involved in this project - and the adjacent development project - hopefully gained some insight into current limitations with their software for implementing the probabilistic approach when applied to a user perspective.
- Previously, only a customised version of the software used in-house had implemented the probabilistic method and simulations. In this project, the researcher used a commercially available beta version of one of the software. Thus, one side of the results was how to improve some aspects of how the software handles the probabilistic approach and provide a more user-friendly interface for modelling the stochastic parameters.
- The designers of energy-saving technology could likely gain some insight from the quantified design decided uncertainties in this project, for which the variation likely could be reduced with increased quality control for products on the market.

4.5.2 Changes in Uncertainties During the Building Process

A possible continuation of this project is to define different variations in uncertainties for the simulations depending on the project phase. For example, earlier simulations should include more significant variations when quantifying uncertainties that when more information is available is updated, i.e. deciding the design or the purchasing process has begun or finished. Another factor can be the parameter uncertainties dependent on workmanship, as discussed below.

4.5.2.1 Quality assurance and quality control (QA/QC)

This study's focus has been on uncertainties partly caused by a lack of QA/QC. Examples of such uncertainties included in the studies are measurements of the floor area, modelling the thermal bridges, and the airtightness performance of the building envelope. Improving the actual energy performance by focusing on these parameters is more challenging than if the cause of the variation was based on the design uncertainty, where it is possible to choose the solution with a better performance. The focus must be on the QA/QC parameter to improve the performance of an evaluated building design—focusing on increasing the quality of products bought or the workmanship quality. One such parameter is the building envelope's airtightness, which depends on the workmanship quality, even when performed according to specification. With increased quality control, possible causes for a deviation in performance are identified, i.e. through blower-door tests and thermal imaging with subsequent measures for identified problems. The overall expected performance could be improved – shifting the distribution lower – while also reducing the variation. The impact of focusing on quality was shown in a study presenting measured data from 100 objects by Svensson [87]. The performance variation for all objects was between 0.11 – 2.5 $l \cdot s^{-1} m^{-2}$, at ±50 Pa, while the objects which focused on quality control during the construction phase accounted for the lower values.

Thus, following the QA/QC process should result in a narrower distribution for factors influenced by the building contractor. Future studies could evaluate and quantify the effect on the actual EP by defining distributions based on measurements before and after measures based on the outcome of the first measurements.

5 Conclusions and Future Work

The investigations and results of this study have identified potential causes for the performance gap and shown the limitations with current deterministic methods used by the building industry for predicting the EP of buildings resulting in the performance gap and causing consequences to the involved stakeholders. At the same time, the examples of several studies have shown the potential of implementing a probabilistic method for predicting the EP and risk level of a building design. The studies also show the current limitations with data and accuracy of the predictive model compared to the actual outcomes and suggestions for future work to improve the predictions.

5.1 Conclusions

The outcomes of this research project contribute to a deeper understanding of how to apply a probabilistic approach to BPS and risk analysis. The main results from this project and the studies performed are the developed PRA method previously described. The main findings have shown how to use the PRA method for data-driven decision support that provides a more complete data set to base the decisions on whether or not the building design fulfils set design criteria. Furthermore, using the method should result in the decision-makers making a more informed decision based on an accurate prediction of EP that includes additional dimensionality not possible with traditional methods. The studies also presented examples of how different stakeholders' perspectives impact the application of the method, how they are affected by the performance gap, and what models to apply to quantify the relevant effects impacting the analysis results.

The outcomes have shown how stakeholders can benefit from using the method. This includes stakeholders in the building industry and the wider society, either when taking the building developer's role or using the as-built building through reduced operational cost. However, in the current form, using the method requires deep knowledge in the field, vast amounts of data, and enough time and computational power to perform the simulations, thus eliminating most from the role of actually applying the method. As a result, users will likely be limited to highly specialised building energy modellers, energy consulting companies, and academia. There is also a risk that the results presented will be the truth for timepressured engineers, i.e. they use it without reflecting on whether it is suitable for the specific application. However, the outcomes have shown the importance of reflecting on the data, the applicability for the specific case investigated, and how to implement the parameter models. An example of this was the use of different levels of detail in the models, the granularity of the zones, and the impact on the parameter model.

The study has shown possible causes for the performance gap based on uncertainties in input data of specific parameters, aggregated uncertainty in predicted EP using simulations, and actual EP using field measurements.

Predicting the performance gap was demonstrated using the identified uncertainties in input data and the PRA method. Using the example of models based on various data quality showed current limitations with the method. In addition to quantifying the probability of failure in attaining the design criteria, implementing the quantification of consequences enables risk analysis. The study also showed how to apply different consequence models depending on the used stakeholder perspective.

The differences between the deterministic and probabilistic methods were also discussed. Examples of the differences include data collection, input data modelling and sampling, building modelling, simulation and the results, the amount of work and time consumed to perform the process, the required computing power, and the possibility for risk analysis. Both methods are dependent on the quality and relevance of the empirical data used as input. The difference is related to the amount of data needed for input and produced as output.

The results presented in this study have shown examples of:

- The prediction varies using the deterministic method dependent on different modellers.
- The actual performance varies in identical buildings.
- The predicted variation in performance using uncertainty analysis.
- Identified causes for and approaches to reduce the performance gap and an understanding of how to achieve it.

Applying the method could result in increased accuracy of the predictions and reduce the confidence gap in BPS.

5.1.1 Dimensionality and Complexity

The probabilistic approach to quantify and predict the EP of buildings introduces a new dimension to the calibration process for the building model and output from the simulations. When using the deterministic method, the calibration process is a one-dimensional process of altering input parameter values, running new simulations -

resulting in a one-dimensional transformation, either an increased or decreased EP - and evaluating if resulting in increased accuracy. A deterministic calibration process gives a reasonably straightforward approach to changing the EP to attain set design criteria. When using a probabilistic approach, the results are in two or more dimensions. Transforming the distributions to fit either the design criteria or field measurements involves shifting and morphing the distribution to the desired shape.

5.1.2 Uncertainty in Prediction and Validation

The process of identifying and quantifying uncertainty by variation in the underlying model parameters and ensuring the data quality to base the distribution on has required a significant amount of time and effort. Nevertheless, the accuracy of the prediction model was not good enough for use in an actual case. In the first version of the method, the probabilistic energy calculation replicated a previous study by Burke et al. [28]. Comparing the results from the two studies showed a reduced accuracy in the replication study. However, this was not likely due to the input data but rather the modelling and software limitations—the study by Burke et al. [28] used novel code to implement the probabilistic approach. In contrast, the replication study used a beta version of the implementation of the code from the previous study, introducing some errors in the probabilistic models for input parameters (of which several now are fixed in the latest beta version), which may have increased the predicted energy use and thus reduced the accuracy of the prediction.

In the second version, applying the method to the multi-family case building, the limitation in an accurate prediction over the whole space was shown. Within a limited subset, the accuracy was adequate. However, since the used input models were limited, the outcomes failed to predict the distribution's tails based on field measurements in the predictions, which resulted in low accuracy.

However, as with all types of data, finding, compiling, and validating the field measurements used to validate the aggregated uncertainty of a building design required a similar amount of work.

5.2 Future Work

Developing and testing the PRA method identified possible aspects, factors, problems, and potential solutions to investigate in the future. Described below is a summary of the identified main possibilities for future work:

A cause for the performance gap in predicting the EP with the current method is that Sweden's current regulatory framework determines deterministic values as input data for stochastic parameters.

However, much work remains before implementing the PRA in the regulatory framework for evaluating the EP of buildings. Although it would require a significant shift in framing the problem and a rework of regulatory texts, it is possible.

Limiting factors in this study resulted in ignoring several uncertain factors. One such parameter is the impact of changes in **future climate**. Since the consequence models defined in this study include costs over extended time frames, this would be a relevant factor to include in future studies. A solution for implementing future climate is through separate climate files created based on climate models to simulate the future energy use for buildings. This factor is vital for building owners and projects where the building contractor is liable for the building's operation for a more extended period.

Another ignored factor is the **deterioration of performance over time**. The relevance of including this factor increases when using new methods and contracts to account for the lifetime aspect for buildings and components, e.g. when the building contractor is required to operate the building for 20+ years, the importance of considering the performance deterioration over time already in the design phase increases.

A separate pilot study [88] measured the long-term performance of windows to evaluate and quantify the effect of the deterioration over time. Again, the results showed significant influence on the performance in specific cases.

In future studies, a focus on quantifying performance deterioration over time for parameters influencing the EP of buildings would be interesting to indicate how the building's EP changes over time. These could be performed using accelerated laboratory tests and long-term field measurements to quantify the effect of performance deterioration in components. This study focused on residential buildings; other types of buildings need to be studied in future work, and specific uncertainties for those types need to be defined and quantified.

The uncertainty quantification process also introduced the problem of **building management** and how this method could clarify the impact of choices made and performed maintenance to improve the performance and reduce uncertainties.

This research project introduced a process for **design optimisation**; however, more work regarding automating the process for design space exploration is needed. Currently, the process requires a significant amount of work and time to produce the results required. In the current form, the application of the method uses a **point-based design** approach, evaluating a single option from the design space and adapting based on the outcome in an iterative process. However, the only limitation to not applying the method using a set-based design approach, where multiple options from the design space are evaluated simultaneously and using an objective function to identify the optimal solutions, is current limitations in computational power. However, others develop methods that focus on design space exploration and have an automated process, i.e. as by Østergård et al. [21].

A guidebook is likely needed to implement and use the PRA method in the building sector, detailing the appropriate situations to apply the method and the gained value.

For the parameters quantified in this study, a question about reducing the variation of a parameter emerged. However, as *Paper II* showed, the variation of a parameter may even be increased to close the performance gap. Introducing or improving **quality assurance procedures** for parameters would ensure that parameters are within expected ranges or could be reduced/increased if more focus is on the quality of these parameters, such as:

- Airtightness control – to identify leaks in the building envelope and between building parts.
- Thermography - to identify thermal bridges, leaks and other problems.
- Ventilation control – to ensure the expected properties and performance
- Moisture measurements - to ensure the expected properties.
- Occupancy related parameters – to ensure using a realistic internal load in the simulations.

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