MSC THESIS REPORT

THROUGH THE WALLS

heat loss parameter estimation of the Prêt-à-Loger house through calibrated Building Performance Simulations

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πάντα χωρεῖ καὶ οὐδὲν μένει

Ηράκλειτος

everything flows and nothing stands still

Heraclitus

Preface

This Master's thesis was written as part of the curriculum of Building Engineering track of the MSc in Civil Engineering at the Delft University of Technology. The research was carried out in collaboration with the BEMNext lab of the Faculty of Civil Engineering and Geosciences, the Faculty of Architecture and the Dutch software development company "White Lioness technologies".

It might seem strange that, although a structural engineer by specialization, I chose to graduate with a subject connected with the fields of building physics and computer sciences. Nevertheless, it is the subject that reached me; though participating with the Prêt-à-Loger team in the Solar Decathlon 2014 competition and through the Special Structures course from the curriculum of Building Engineering. The first, was a wonderful 2-year journey through designing and constructing, with a team of 50 students and advisors from TU Delft, our dream solution for the problem of energy consuming terraced houses in the Netherlands. The second, was my initiation to the magic world of computation and software development, which continued with further courses and finally, by joining the "pack" of White Lioness technologies.

With this, I would like to warmly thank the people that supported me through all these journeys.

Jeroen and Anke for being my mentors for the software and optimization subjects of the thesis, acting as daily supervisors and organizers of my work and above all, for believing in me and my will to follow them towards the BEMNext vision.

Andy for his leading role in the Prêt-à-Loger revolution, for kindly granting me access to the measurements of the house and for chairing my committee.

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Jan-Pieter for his advices in the formulation of the thesis subject, for the structure of this report and for sharing his insights from the construction industry.

My friends and my colleagues in White Lioness technologies for encouraging me all this time.

Finally, this study is dedicated to my parents, for their own, endless dedication in all the years of my life.

Georgios Xexakis

Abstract

The calculation of a residential Energy Label in the Netherlands and the payback time of an energy refurbishment are often affected by various inaccuracies between theoretical and actual achieved energy consumption. Even if improvements are attempted on either of them, significant problems occur such as the accuracy of input data for the simulation or the large duration of sufficient measurements. According to the latest research, a significant uncertainty is stemming from the calculation of the space heating requirements. The goal of this study is to increase the input data accuracy for some of the most influential parameters for this calculation, focusing on those depending on the characteristics of the building envelope. These include the U-values of building elements, infiltration factors and the solar gain factors of the windows.

To achieve this goal, an automated process is developed, where by calibrating an energy simulation model (BPS) of a house with a sample of actual measured data, an estimation of its real parameters can be produced. This is then used to verify its design, assess the efficiency of its building envelope and create the basis for estimating its yearly energy consumption. The measured data is originating from monitoring the Prêt-à-Loger house, a prototype refurbishment system designed with the intention to render the terraced houses of the Netherlands energy neutral.

A sensitivity analysis is first conducted to estimate the relative importance of each parameter in terms of simulation error and energy. The process then succeeds on indicating some difference between live measurements and the simulation produced by the parameter values documented in the design. By treating these parameters as unknown, a model calibration process is set to find them, as in the case of an old house where material properties are lost or undocumented. The process is finally resulting on an adequate range of as-built parameters, validated against further measurements with an acceptable error.

Acronyms

Pal House	Prêt-à-Loger house
BPS	Building Performance Simulation
API	Application Programming Interface
MBE	Mean Bias Error (%)
RMSE	Root Mean Square Error
CV(RMSE)	Coefficient of Variation of Root Mean Square Error (%)
ACH	Air Changes per Hour
KNMI	Koninklijk Nederlands Meteorologisch Instituut (Royal Netherlands Meteorological Institute)
cond	Opaque envelope equivalent conductivity (W/m^2K)
inf_coef	Cracks flow coefficient ($m^3/s/m^2$)
inf_exp	Cracks flow exponent (non-dimensional, ranges from 0.5 to 1)
trans	U-value of transparent envelope (W/mK)
solar	Solar gains coefficient (non-dimensional, ranges from 0 to 1)

Contents

1. Introduction

1.1 Existing housing stock

If the spirit of an era in the Architecture, Engineering and Construction (AEC) sector could be captured with just a few words, today one of them might be “Sustainability”. Nevertheless, one great paradox of the sector is that is still mainly preoccupied with designing and sustainable new buildings while existing old buildings represent the largest part of the current building stock. Especially in Europe this percentage can reach above 90% with some constructions originating centuries ago and still being in use.

Furthermore, the existing buildings are also largely responsible for the energy problem of the planet. They account for a significant part of the total energy demand, reaching e.g. 39% in the US (EPA, 2008) and UK (DECC, 2010) and 41% in northern Europe. For the latter countries, the largest part of the total energy use, almost 30%, is being used in existing residential buildings (Meijer, 2008), underlining their significance in the energy reduction challenge of the future.

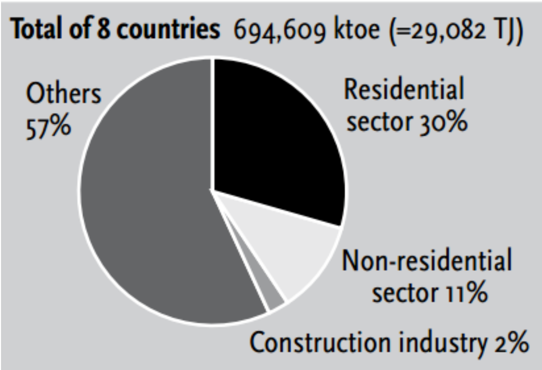


Fig. 1: Energy use of 8 northern European countries in kiloton oil equivalent (ktoe) and TeraJoule. Graph from Meijer (2008), data from Eurostat and IEA

This challenge is further formalized by the European Union goal of 20-20-20 i.e. 20% reduction of CO2 emissions, 20% more energy coming from renewable and 20% reduction of energy consumption by 2020 (Hensen and Lamberts, 2011). To achieve this goal and the even stricter ones set for 2050, a major reduction of over 60% in energy consumption of existing houses should be accomplished in a short amount of time (Konstantinou, 2014).

For the Netherlands, this reduction goal is mainly affecting the row or terraced houses (doorzonwoning), one of the most numerous building typologies in the country. These houses form about 42% of the current building stock while according to Eurostat (2011) 6 out of 10 residents of Netherlands are staying in a row (or terraced) house. Furthermore, this typology can be found in large numbers in Scandinavia, UK and Germany.

Fig. 2: Row-house typology in the Netherlands (domotica.nl, 2014)

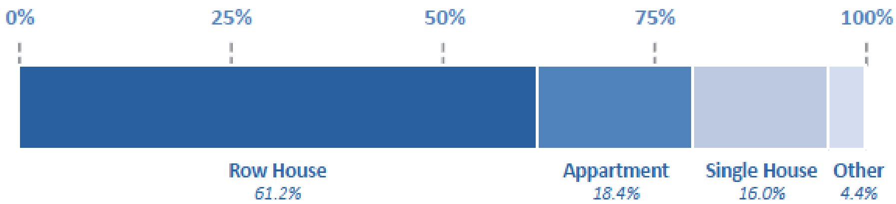


Fig. 3: Percentage of resident per housing typology in NL. Graph from Pret-a-loger (2014), data from Eurostat (2011)

But apart from being a very large typology, it is also one of the most energy inefficient. Almost half of these houses were built after the 2nd World War as a fast and inexpensive solution for the housing shortage problem (Pret-a-loger, 2014) and with energy design being still an unknown design factor. Subsequently, after more than 50 years of use these houses are not satisfying the current energy efficiency demands, as reported by Heijneman and Ham (2004).

The above inefficiency combined with a sheer number of 1.4 million dwellings, suggest that one major success paragon for the energy reduction goals in the Netherlands can be the energy upgrade/refurbishment of the existing row houses. Furthermore, to be able to achieve the initial goals of 2020, their refurbishment rate should increase and become even more effective. But even if its significance is evident for many years now the rate is still low, while efficient and integrated solutions are very slowly adopted by the market and designers.

1.2 Energy labelling in the Netherlands

Background

As a logical starting point for the energy refurbishment of any building type, an evaluation of its current situation and an estimation of the target situation should be conducted. The current policy in the Netherlands has the form of Energy Labels, similar to those for the efficiency of appliances, and is based on the European Performance of Buildings Directive (2002), (2010). In this, among other policies to achieving the targets of EU for energy reduction in the building sector, an energy certification system for all new and existing buildings was outlined. For residential buildings, it was implemented as mandatory certification at least for all the new, sold or rented properties (Majcen et al., 2013b). In general, one of the main targets of this certification is to promote the building of energy efficient new buildings and the energy refurbishment of the existing. The detailed implementation and publishing methodology of this certification is varying among the member states as well as its effectiveness and results (Andaloro et al., 2010). The results were analysed by numerous EU projects and initiatives and some of the shortcomings indicated were the absence of sanctions in case of no compliance with the directive and its generally looseness which were open for interpretation (Campaigning for the Future, 2010). For the last part, there was an effort from CEN to produce a series of standards for harmonizing the different methodologies of the member states which was met with limited success (Andaloro et al., 2010).

Apart from the EU projects, numerous studies were made by researchers to evaluate the theoretical results of the EPC methodology (Energy Performance Coefficient, the precursor of Energy Label) in comparison with the actual results. Furthermore a number of models were proposed to explain possible differences such as the 'rebound effect' (Berkhout et al., 2000) where the underestimated theoretical energy consumption may be partly explained by the fact that the use of efficient technology in buildings may reduce the energy bills but may also encourage the increase of consumption. As summarized by Majcen et al. (2013b), significant discrepancies were found in many of these studies and this is partly explained by the authors from the fact that are just an estimation of the actual consumption. Specifically, the actual lifestyle of the occupants is not taken into account in the EPC/Energy labels and simplified models are used to describe the physical properties of the house calculate its energy consumption. However, it is pointed that these certificates are used for choosing possible energy-saving measures and estimating their efficiency as well as for calculating the pay-back time for investing in these measures. There is even an example of 'green bank' that invests on energy refurbishment measures on the base of the estimated efficiency of the solutions (Triodos Bank, 2014) Even more importantly, these theoretical energy consumptions are also used for formulating energy reduction policies and targets, thus raising questions about their real feasibility.

Jointly with the applications of the directive for certifying the energy consumption of the buildings, a number of targets have been set in European level to reduce the primary energy use by 20% by 2020, and the CO2 emissions by 30% by 2020 and 50% by 2050. In the Netherlands, which is in the forefront of the European residential sector for energy efficiency measures (Energy Efficiency Policies, 2012), these targets were translated to a variety of programs between different stakeholders; from the 'Meer met minder' (translated as More with less) between the Dutch government, corporations and external construction companies to the 'Convenant Energiebesparing Corporatiesector' between the Dutch housing associations, different targets were agreed in order to promote energy efficiency in buildings until 2018-2020 (Majcen et al., 2013b). A summary of these saving targets can be seen in Table 1.

Programs	Agreed savings
Convenant energiebesparing corporatiesector	−24 PJ primary energy
	−20% Gas use
Meer met minder	−100 PJ primary energy
	−20–30% Primary energy
SERPEC-CC	−19% Primary energy
IDEAL	−10% Primary energy
Dutch government	−16% CO_2
EC action plan for energy efficiency	−27% Primary energy

Table 1: Agreed saving targets in NL and EU (Majcen et al., 2013b)

Problems with the Energy Labels

Even if the deadline for most of these targets is closing fast, the number of certified Energy Labels in the residential sector in the Netherlands is still low. According to the Dutch Central Bureau for Statistics (CBS, 2012), in the end of 2011 the number of energy labels was 2 042 714, which was a bit more than a quarter of the total dwelling number of 7 217 803. It is also mentioned that the energy label number rise for more than a quarter from the number in the end of 2009. Nevertheless, assuming the same or significantly larger rate of labelling, it is unlikely that the percentage of certified dwellings in the end of 2014 can reach even half of the total number. A distribution of the energy labels per year and per dwelling number can be seen below. As was mentioned also before, the large percentage of the lowest Energy Labels E, F and G can be noted, for dwellings built post-war and up until the 1980s.

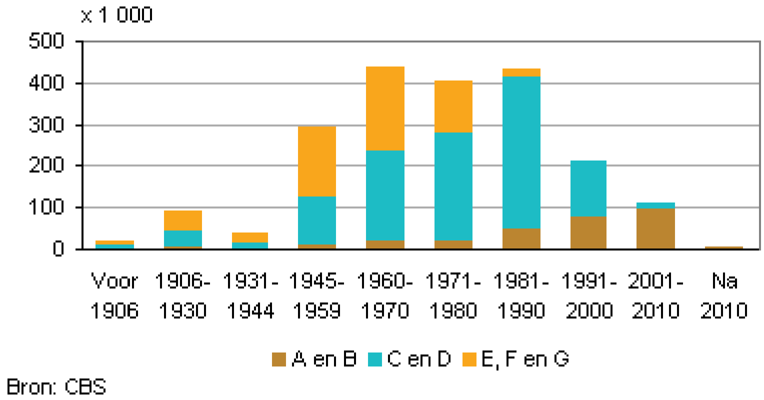


Fig. 4: Comparison of certified Energy Label with building year per dwelling number in NL (CBS, 2012)

Based on the above distribution and taking into account also the housing type and size, an estimation of the Energy Labels of the total dwelling stock was performed by the government in order to be used as a provisional certificate from 1st of January 2015. This was decided in order to increase the significance of the Energy Label in the property market, especially for the owner-occupied dwellings where in 2009 almost for 90% of transactions the parties ignored the energy labels (wegwijs.nl, 2014), as there is no sanction for doing so. The current difference between estimated and certified labels for the country and for a large city such as The Hague are illustrated in the following figures. From them they can be observed the small percentage of certified labels and the large density of 'red' dwellings (Label G) in the centre of Den Haag and other large cities. The last observation may also support the idea that these dwellings are in need of extensive and careful energy refurbishment, especially in the culturally protected centre of the cities.

Fig. 5: Estimated (top) and certified (bottom) energy labels in the Netherlands in 2014

(Energielabelatlas, 2014)

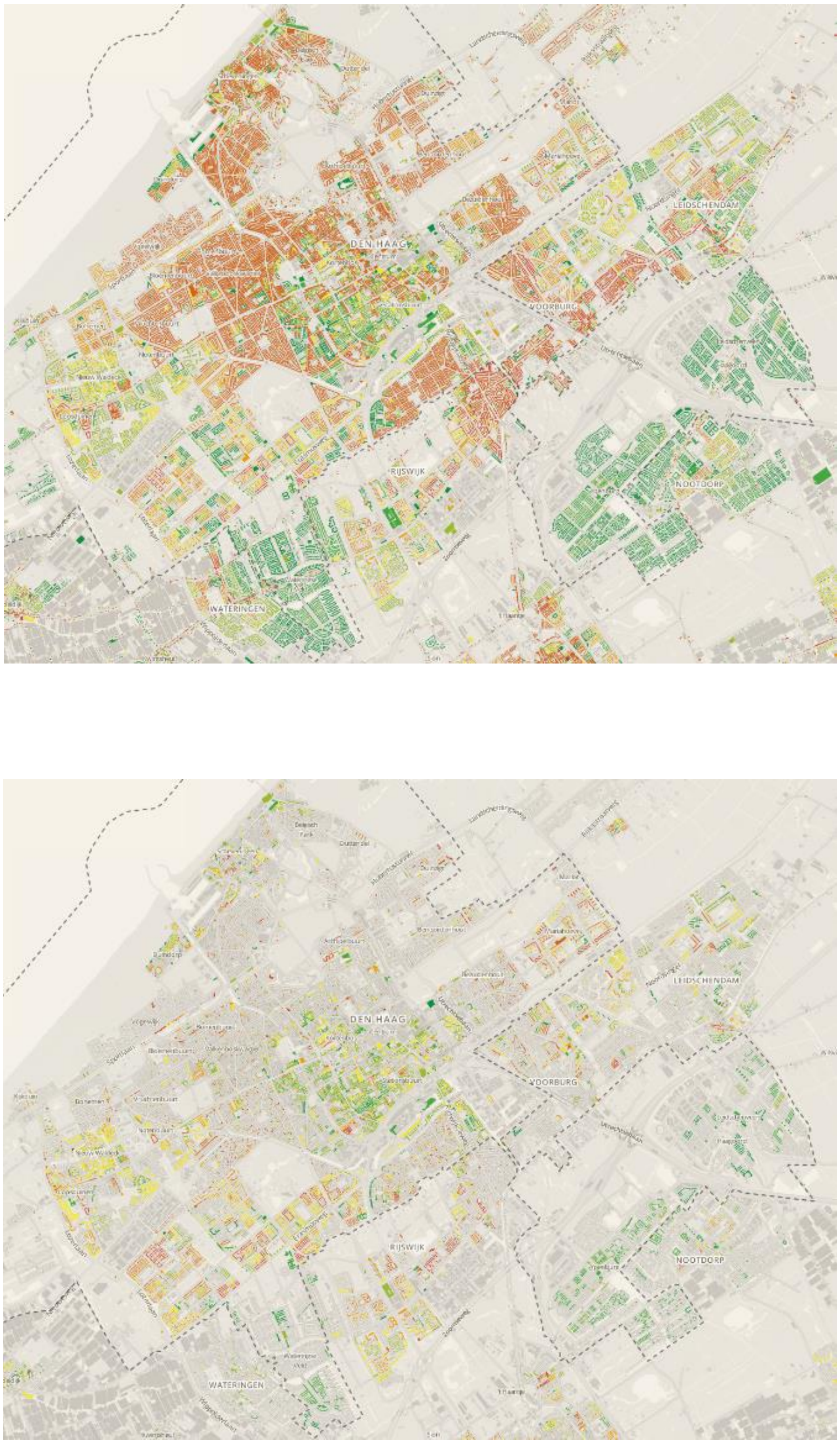


Fig. 6: Estimated (top) and certified (bottom) energy labels in the metropolitan area of the Hague in 2014 (Energielabelatlas, 2014)

Unfortunately, even for the dwellings with certified energy labels, the estimation is not always accurate. Findings from Majcen et al. (2013b) after comparing 193 856 cases of issued energy labels on 2010 with the actual measured energy consumption for the same dwellings, show significant discrepancies. These discrepancies are summarized per year in the following figures, for gas and for total primary energy consumption per label and for gas per heating equipment.

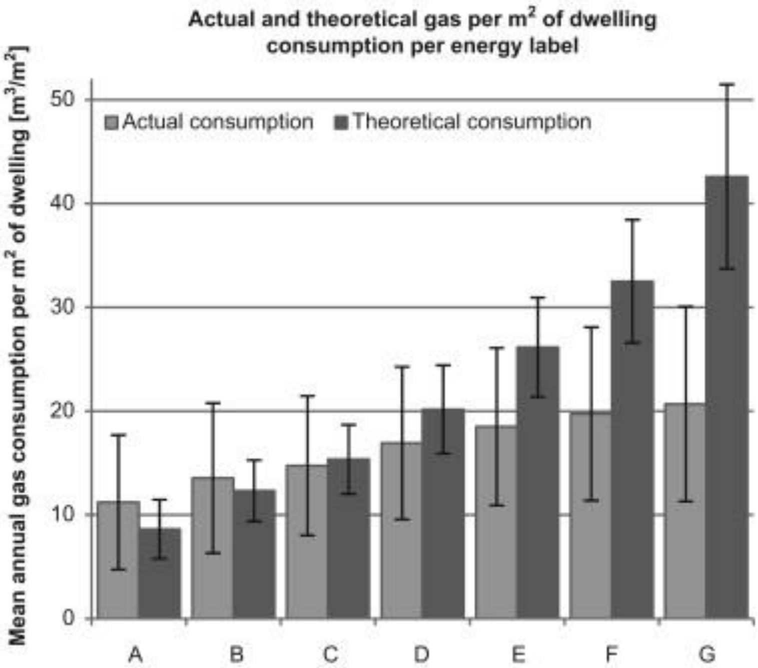


Fig. 7: Actual and theoretical gas consumption per m2 of dwelling area per label. (Majcen et al., 2013b)

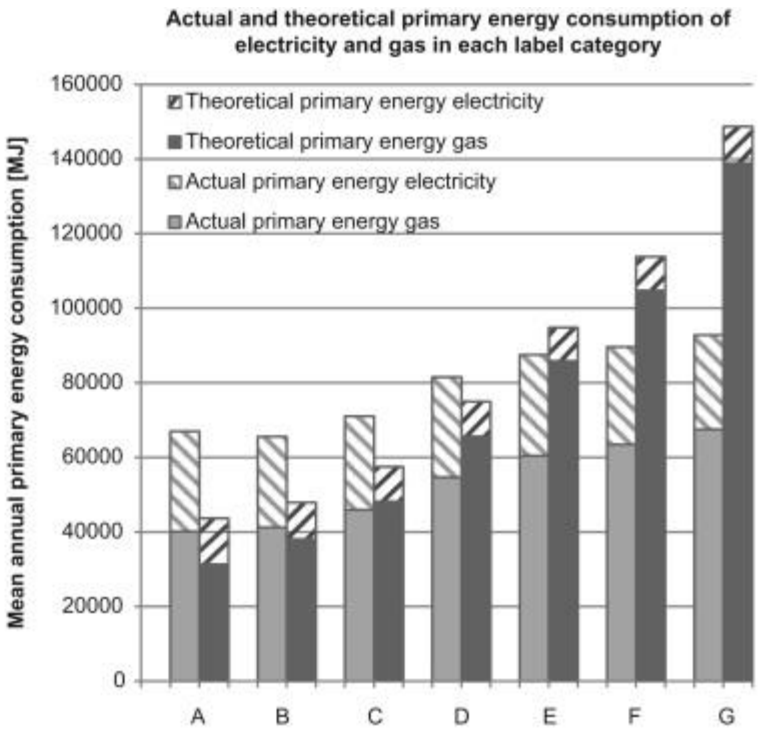


Fig. 8: Primary energy consumption in different label categories.(Majcen et al., 2013b)

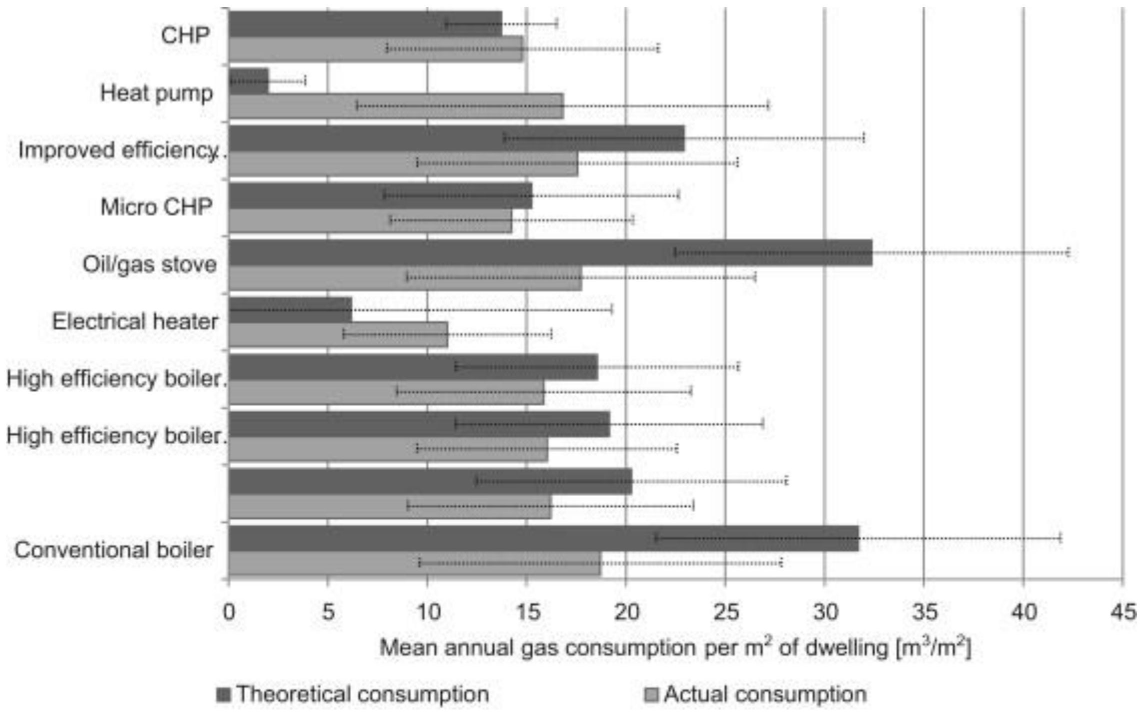


Fig. 9: Gas consumptions per m^2 dwelling per installation type with ±1 standard deviation (Majcen et al., 2013a)

As shown from the above results, gas consumption is overestimated for the lower Energy Labels (D-G) and underestimated for the higher Energy Labels (A,B). Also, the significant deviation of results should be noted, especially for the actual energy calculation where it can be even 50% higher or lower from the average values. As for electricity, there is a significant underestimation of primary energy needed which is quite constant among the different labels and can be possible explained from the fact that household appliances are not included in the theoretical calculation. Finally, for the different heating devices it is shown that in dwellings with conventional and high efficiency boilers or even gas stoves the gas consumption is overestimated while for electrical heaters, CHP and heat pumps it is underestimated. Especially for the heat pump the range between the theoretical and actual consumption is quite significant, with the average value for the actual to be slightly more than a high-efficiency boiler.

In an effort to explain these discrepancies in gas consumption, a follow-up paper from the same authors (Majcen et al., 2013a) investigates the reasons behind them by using descriptive statistics, regression analysis and sensitivity analysis. These reasons include the possible effect of the assumptions in the calculation method and the accuracy of the inspection data that was the input to the model. For the second part it was found from the sensitivity analysis that the influence of the input parameters varied significantly.

Specifically:

- The parameters with high influence are:
    - the average indoor temperature
    - the ventilation rate
    - the accuracy of U-value

- The parameters with rather limited impact are:
    - the number of occupants
    - the internal heat load

Furthermore, regression analysis explained less successfully the variation of the actual consumption rather the theoretical and showed that influential parameters for the actual such as floor area, salary and ownership type had a far less influence to the theoretical calculation. As for the heat pump, electrical heating or CHP consumption underestimation, it is suggested that might be due to the missing data for hot tap water, flaws in the inspection phase or other possibly weak assumptions made by energy companies when measuring the gas. A general trend that is also suggested is that the less efficient the installation system the higher the overestimation.

Another important conclusion of the study is that the assumed reduction when improving an energy label from G towards A might be much lower in reality. These possibly inaccurate estimations may affect significantly the following:

- the pay-back time for measures towards energy-efficient dwellings
- the aforementioned targets set in Dutch and European level for reduction in energy consumption and CO_2 emissions

Especially for the last, it was discovered in the first study, that “even if the whole Dutch housing stock were refurbished and upgraded to an A label (which would in itself be an unrealistically ambitious undertaking), the actual primary energy savings would not meet most of the current targets”. Nevertheless, if the theoretical values are used, most of the targets for both energy and CO_2 levels are achievable, leading to possibly false conclusions about the set policies and used methodologies.

1.3 Solar Decathlon and Prêt-à-Loger

The Solar Decathlon is an open competition between higher education student-teams from all over the world that challenges them to design, build and operate a solar-powered ‘green’ house (US Department of Energy, 2014). The challenge is multi-faceted, as the competition includes 10 different sub-contests that ensure the design and construction of a very well integrated house that can be energy-efficient, attractive and affordable. In the last edition of Solar Decathlon Europe in Versailles, France, a multi-disciplinary team from TU Delft called Prêt-à-Loger (translated as “ready-to-live”) participated in the competition with a proposal that focused more in the existing housing stock rather than a new house type. More specifically, the starting point for the team were the post-war row houses, with all their problems that were mentioned above, and the challenge to make them more energy efficient and comfortable while creating new quality space. For addressing this, a case study of such a house was chosen from the small town of Honselersdijk, a bit northern of Delft. The house had the special property of being the paternal home of one of the team-members, offering more to the concept of “Improve your house, preserve your home” that was adopted by the team (Pret-a-loger, 2014). The house was estimated as having an Energy Label of ‘E’, while the typical energy cost was measured to 175 euro/month.

Fig. 10: The original case study row house (Pret-a-loger, 2014)

The concept for the energy refurbishment of the house was mainly based to an external, integrated intervention system called ‘The Skin’ (Pret-a-loger, 2014). This system includes for the north side the replacement of one brick layer and cavity with 300mm of high-efficiency wood fibre insulation for the wall along with an insulated green roof. On the south, a glasshouse-like structure that combines energy generation through integrated PV-panels, a buffer space that generates heat from the sun and protect*s the house and also, a quality extra space for the house, with multiple uses throughout the year. Supplementary, a heat-pump coupled with thermodynamic roof panels is used to cover the space and water heating, while a home-automation system is installed to control the windows and sun-shading of the house and most importantly, measure and regulate the energy consumption, production and comfort of the house.

Fig. 11: The south side of the prototype house, featuring the integrated glasshouse

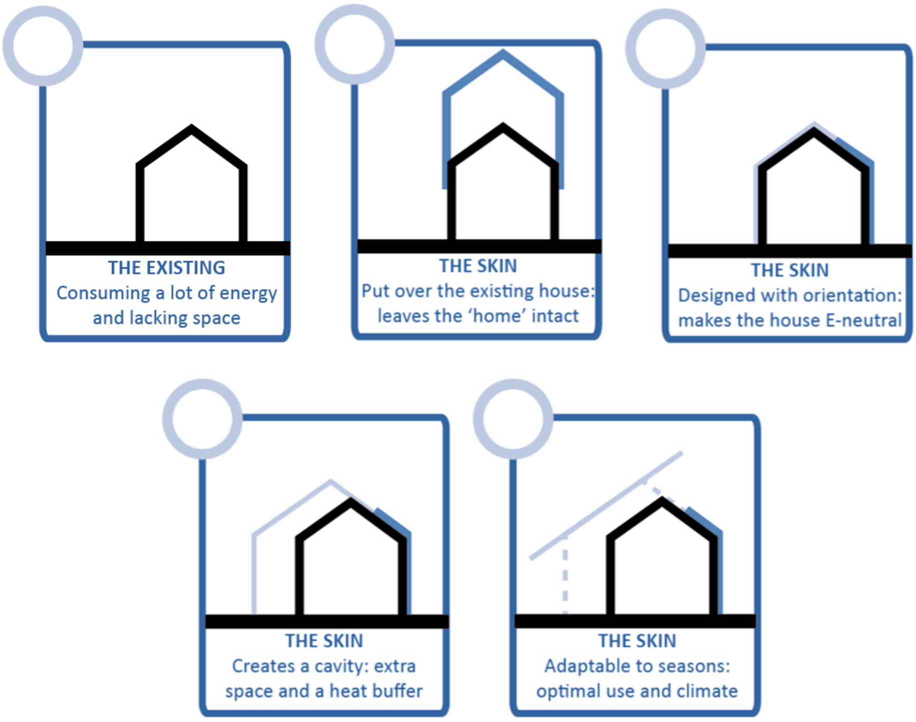


Fig. 12: PaL refurbishment design concept

More information on the competition and a technical summary of the house can be found in appendix 9.4. Finally, it is noted that the Prêt-à-Loger prototype in Delft is further abbreviated as the 'PaL house'.

2. Problem analysis

The issues suggested in the introduction are formulated in the following problem statement of this study. Based on the background research found in the appendices Section 9.1, a research proposal is then suggested to tackle the problem. The proposal is furtherly analysed through research questions that are also answered in the course of this study.

2.1 Problem formulation

The problem formulation is resulting as a summary of:

- the apparent need for energy refurbishment of the post-war row houses in the Netherlands
- the aforementioned problems in the Energy Labelling certification system

From the analysis of Majcen et al. (2013b) it can be observed that even if there are many initiatives from the public or private sector to promote energy refurbishments and new efficient buildings (as those found in Table 1), the targets set and the progress made towards them are not reflecting always the truth.

As analysed above, the indication for this is mainly stemming from the comparison between the actual-measured and theoretical-simulated values of energy consumption. Therefore two boundaries solutions could be suggested:

- **Increase the accuracy of the actual data measurements**. Understand the distribution of the energy consumption per household and per appliance/equipment and design measures in order to limit it. Measure comfort inside the house in order to establish a better connection between the investment for it and the result achieved. Thus the energy label system and the targets set for energy reduction could be based on actual data and be more reliable. On the other hand, to draw accurate conclusions about the energy consumption of a dwelling, the continuous monitoring for a duration of at least one year might be necessary. The same might be true for the energy-efficiency certifications, as e.g. a housing corporation that wants to refurbish their properties to Energy Label A and rent them as such would have to prove that they really can reach such low energy consumption by measuring them for a long amount of time.

- **Increase the accuracy of the energy simulation model for the theoretical data.** Even from the 1970s, researchers and industry have made a lot of suggestions, models and methods on how to achieve the above (Coakley et al., 2014). In a very simplistic formulation, the solution could be split on measures to improve the model – calculation method itself and measures to improve the input parameters. For the first, it was mentioned also above that the simple calculation model and assumptions used (e.g. about the heating surface area that is taken as the total area) (Majcen et al.) might not be appropriate for every house. As for the input, there are many ‘unknown’ or difficult to find parameters, such as the U-values of the walls, the rates of ventilation and infiltration, the user behaviour etc. Especially the first three, which were also mentioned in the study by Majcen et al. (2013a) as high influential parameters, can be associated with the heat losses of the envelope, a key factor in estimating the energy needs and consumption of the house.

  A possible solution could be then to use one the state-of-the-art simulation methods (e.g. dynamic simulation) which can model the actual conditions and consumptions in much more detail in order to estimate the yearly consumption of the dwelling. A notable example is the EnergyPlus information which is discussed in detail in Section 9.1. Unfortunately, to achieve a better output, the input should also be of similar detail and quality. Especially in dynamic simulation programs, this is very expensive as even hundreds of parameters should be fine-tuned in order to achieve a good result. In the usual practice that would be done by an engineer, manually configuring all the parameters and using most of the time assumptions and generalizations, without having an easy way to validate the results.

Problem statement

The calculation of an Energy Label consumption target and the payback time of a residential energy refurbishment are often affected by various inaccuracies between the theoretical and actual achieved energy consumption. Even if improvements are attempted on either of them, significant problems occur such as the accuracy of the input data for the simulation or the large duration of the measurements.

2.2 Research proposal

Premises

The opportunity behind the extensive experimental infrastructure of the PaL house and its monitoring system can make it a fit candidate to use as a study for a possibly improved solution on the problem statement above. Furthermore, the fact that the house represents a newly refurbished post-war dwelling enhances even more the choice for it. Many typical technologies that are used in most of the current energy refurbishments are also present, such as a heat pump, mechanical ventilation, PassivHaus rate insulation as well as more experimental, such as the glasshouse buffer zone, integrated with the PV and thermodynamic panels.

As for tackling the problem statement, a middle ground between the outlined boundaries can be suggested. Specifically, a solution that can combine efficiently both the detailed dynamic simulation of the Building Performance Model (BPS) and the accurate measurement of the actual conditions and consumption of the dwelling. By taking a representative sample of measured data (thus avoiding the yearly monitoring) and comparing it with the results of the simulation, the assumptions and the input parameters could be iteratively calibrated in order to improve the data fitting of the theoretical results. Due to this iteratively character it would be best if the above process could be automated and structured as an algorithm in order to improve the prognostic value of the BPS model.

Focus point

As mentioned in the problem analysis, one of the most important characteristics of the dynamic simulation method is the plethora of parameters used to create the model. The problem of entering all these parameters in a calibration algorithm is well researched and many methods have been proposed to tackle it, as mentioned in the review from Coakley et al. (2014). Still, according to the same review, the requirement of that many parameters is a drawback for the accuracy of the simulation method, often leading to very complex solutions.

Based on the relevant research findings on the residential stock of the Netherlands from Majcen et al. (2013b), a focus on the most influential parameters for this typology can be suggested, such as the U-values or the ventilation rates. These parameters are associated with the space heating energy, which for the Dutch houses can reach 34% of the total energy use, according to recent surveys (Energiezaak et al., 2011). This renders it the highest consumption factor, with energy for cooking and cleaning following. More information on this subject can be found in the background research in the appendices in Section 9.1.

Following the Dutch calculation process for Energy Labels (ISSO, 2009), the space heating energy depends on the efficiency of the heating and distribution systems (e.g. heat pump, piping and radiators), the existence of auxiliary systems such as a solar boilers and most importantly, on the space heat demand. In engineering terms, this can be taken as the main “load” to design a heating system.

From the same process, the calculation of the total space heat demand in a house is given as:

$$Q_{space\ heat\ demand} = Q_{transmission\ loss} + Q_{ventilation\ loss} - Q_{internal\ gains} - Q_{solar\ gain}$$

(Eq. 1)

The different parameters on this equation are analysed shortly below, while a more extensive analysis with the corresponding equations can be found in the methodology Chapter 23. The analysis is based on building physics theory (Linden, 2013) and the background research of Section 9.1.

- Transmission losses depend on the temperature difference, the area of the building envelope and the U-values of the different elements, such as floors, walls etc. The U-values are specified in the design phase of the building and --affect the number and thickness of material layers of the elements. Nevertheless, these target values can be affected significantly by the quality of the construction and phenomena such as thermal bridging, leading possibly to a wide range of transmission losses. They can also depend on user behaviour through the temperature setpoint that is used.
- Ventilation losses result from both the ventilation needed for refreshing the air inside the house and the “unwanted” ventilation, the infiltration of air through cracks in the building envelope. They depend on a variety of factors. For the first, it mainly depend on user behaviour and comfort conditions in the house (e.g. ventilate on stale air or on unwanted thermal conditions). Its estimation can prove a challenge, especially when natural ventilation is used, as in most of the Dutch houses. Even if mechanical ventilation is used, where the ventilation rate is known and thus also its corresponding losses, infiltration can still be an unknown factor. It depends on the building envelope air-tightness and factors such as wind speed and temperature difference with the exterior. As in the case of the U-values, the air-tightness of the envelope is affected by the construction process as well as the manufacturing the elements.
- Internal gains result from house lighting, equipment use, the number of the occupants and their activities etc. They are affected mainly by the user behaviour and the technical characteristics of the heat emitting equipment of the house.

- Solar gain is the total amount of heat due to solar radiation passing the transparent elements of the building envelope. It can also be affected by the user e.g. through the use of blinds or sunscreens or even leaving the glazing dirty. From the building envelope point, it is affected by the Solar Heat Gain coefficient of the transparent element, noted as g in the general building physics theory or ZTA in the Dutch bibliography.

Additionally to the above formulation, the following points should be taken into account.

- Restrictions in measuring accurate (residential) user behaviour in the Pal House
- Capabilities of the available monitoring system
- Limitations in the scope of the current study

Therefore, a focus is proposed on the parameters that depend on the construction characteristics of the building envelope. That is, the U-values of the elements, the infiltration rate and the solar gain coefficient of the transparent elements. This would allow to concentrate first on the more “static” side of the simulation problem and increase the accuracy of many influential parameters for residential buildings. In that way, their uncertainty could be decoupled from the factors that depend on user behaviour, installation efficiency etc., allowing for their separate study and improvement in a next stage.

Therefore, it is noted that the measured data should be filtered to find the periods that the house is on “free run”. These periods are selected on minimum user presence in the house, on avoiding un-monitored ventilation and any other interference on the house ability to keep its heat.

Space heating parameters in Pal House

The main heat loss parameters are shown in the following figure, grouped in relevant categories. Their parameters are denoted accordingly for their availability in the Pal House.

- **For transmission losses**, the area of external surfaces is known with satisfying accuracy through construction plans and on site measurements, while the temperature difference between exterior and interior can be measured through the monitoring system. On the other hand, U-values can be denoted as an uncertain/unknown parameter, for the reasons mentioned above and in the background research.
- **For infiltration losses**, the infiltration factor can also be characterised as uncertain. It has to be noted, that although it is a dynamic factor depending e.g.

on wind direction and velocity, temperature differences etc., in many simulation methods it is taken as a static value. It can be also directly measured through a blower door test or by testing the concentration of e.g. CO2. Thus, there is opportunity in a possible calibration process that could take into account the conditions of many different time periods to possibly yield a better estimation of an infiltration factor.

- **For ventilation losses**, the ventilation rate can be measured when mechanical ventilation is used, while natural ventilation is avoided for the purposes of this research. It is noted however that in the design goals of the Pal house, natural ventilation is playing a significant role in transferring heat from the glasshouse in the house and can form a possible subject for a following research.

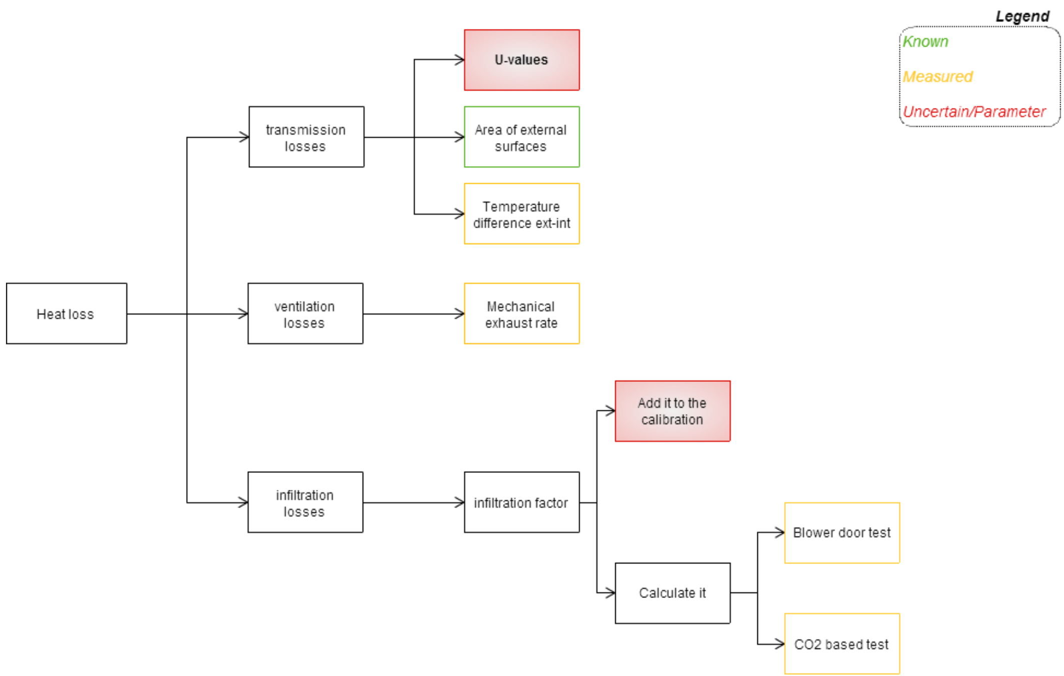


Fig. 13: Heat loss parameters

As for the solar gain coefficient, it depends mainly on the glazing used in the construction. This is a known value from the manufacturer, as well as the U-value of the windows, but still it can be verified.

Main proposal

Develop an automated process for calibrating a BPS model of the Prêt-à-Loger house with a sample of actual measured data, in order to verify its design, assess the efficiency of its building envelope and create the basis for estimating its yearly consumption.

Research questions

From analysing the main objective and after the initial background research (found in appendix 10.1), the following research questions are proposed. In this study, they are answered using the PaL House, but they are formed in a more general way. That is to show that they could be possibly applied, with some modifications, to other houses or even different typologies. Nevertheless, it is stressed that their validation for the specific case study is only an indication for the more general application and not a proof for it. It is also noted that the questions are structured as use cases of the aforementioned calibration process.

How the process could be applied in case of:

1. A new or extensively refurbished house, where the properties of the building envelope are indicated by the designer, as e.g. in the prototype Pal House?
2. An old house, where the properties of the building envelope cannot be easily indicated due to a variety of reasons e.g. lost construction plans/report, non-uniform material properties, ageing, damages etc.?

Other relevant secondary questions are also proposed:

- How large should be the measured data sample used for calibration? Are one or two weeks enough for estimating the parameters accurately?
- What is the importance of each relevant parameter?

3. Methodology

In the following the methodology and the starting assumptions for the various aspects of the research proposal are formulated and analyzed. The chapter starts with high-level diagrams of the two processes as mentioned in the research questions and continues with the used strategies for the modelling, calibration, verification and software development of this study.

3.1 New house process – Design verification

A high-level process for the verification of a new house design is proposed in the following diagram. Measured data from the house monitoring is extracted for selected periods. An EnergyPlus simulation model is created by the DesignBuilder graphic interface by using the collected building data. The climate data corresponding to the measured periods is extracted from the website of the meteorological service of the Netherlands (KNMI) and used to simulate these periods. The output of the simulation (temperatures) is compared with measured data and the error metrics are reported.

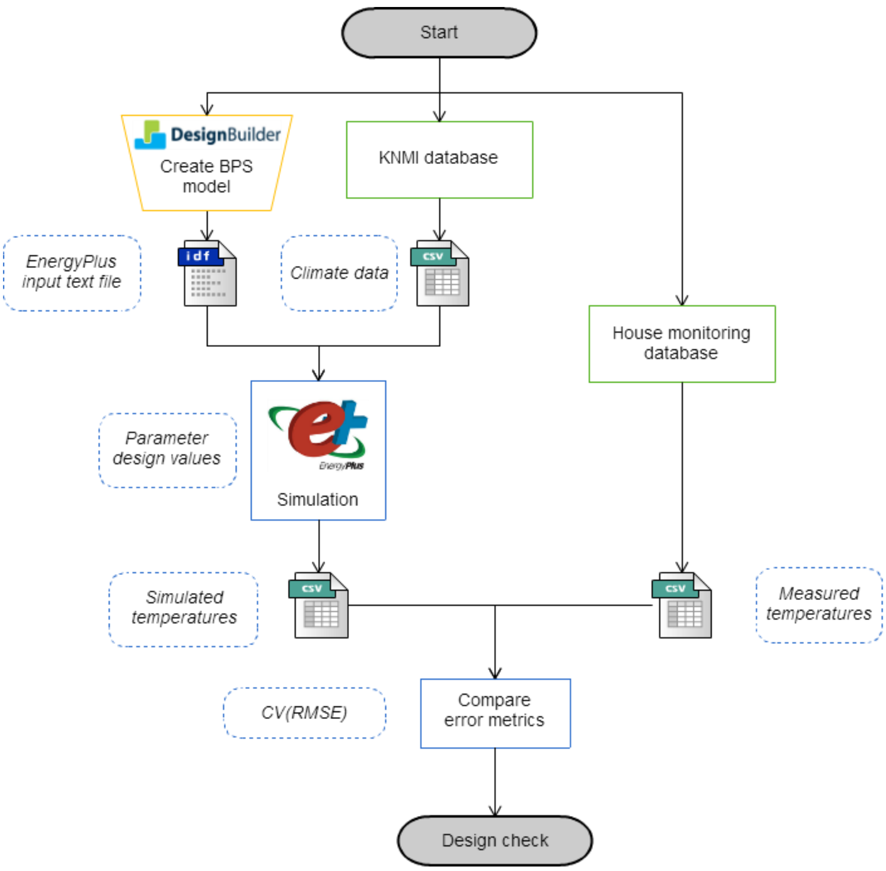


Fig. 14: Verification process diagram

3.2 Old house process – Parameter calibration

A high-level process for finding parameter ranges of an old house through model calibration, is proposed in the following diagram. As mentioned, it is using as inputs the weather data from KNMI, measured data from the monitoring and a simulation model derived from collected building data and yields as an output a calibrated model, through an algorithmic loop (more details on Section 3.3). This process is modified to align with the goals of the thesis and the special requirements of the Pal House. A more detailed methodology can be found in the appendices Section 9.9.

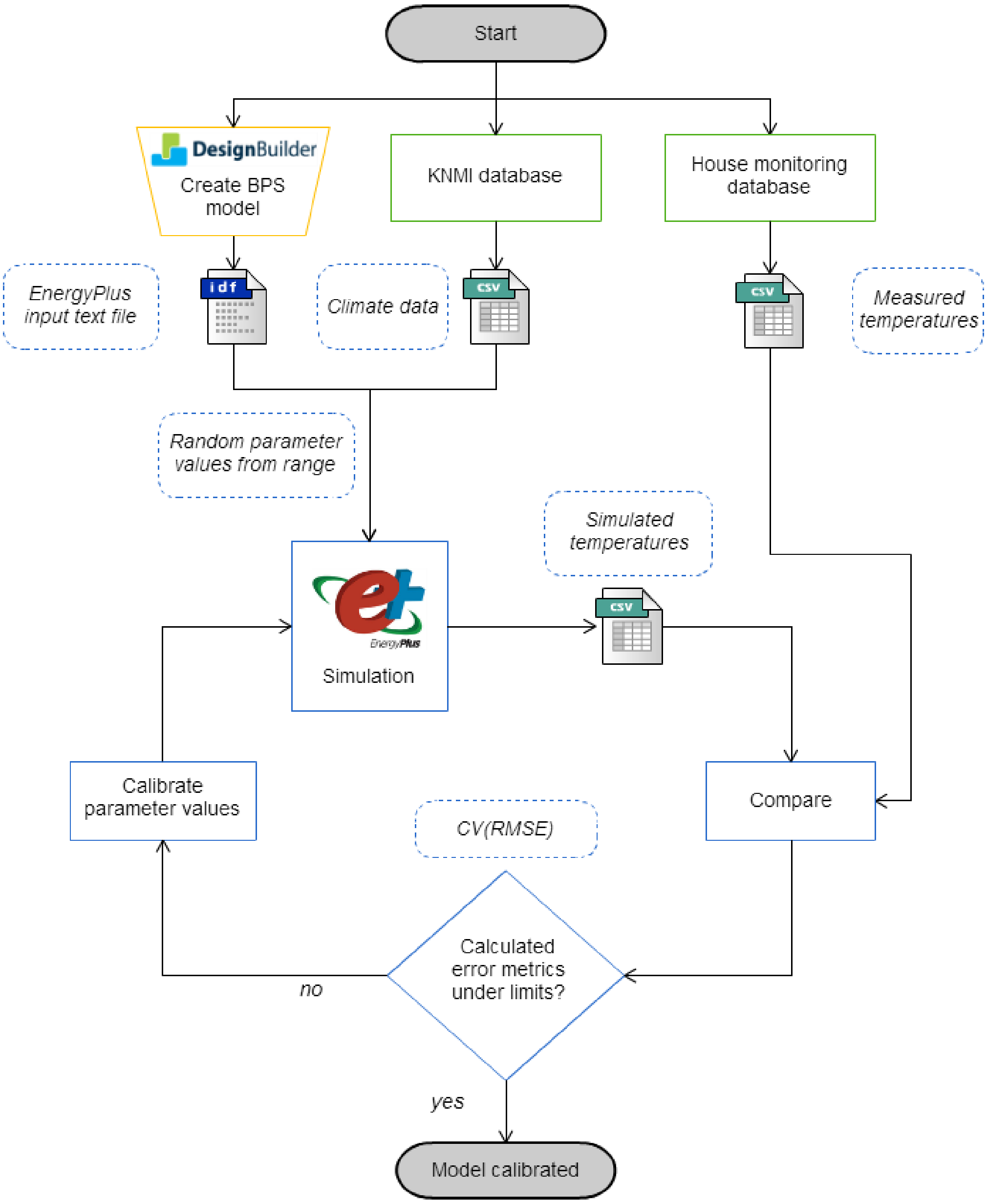


Fig. 15: Calibration process diagram

3.3 Calibration algorithm

As can be found in the background research Section 9.1 and the relevant references, there is a large variety of possible methods to calibrate a BPS model to measured data (Coakley et al., 2014). The reasoning behind selecting an appropriate method stems from the premises of the main proposal and the research questions of this thesis.

The main points are:

1. The solution of the calibration should be able to form the base of a prognostic model for the house.
2. The calibration parameters should be connected with physical properties of the building and its elements, in order for the results to be comparable with other methods (e.g. with the Energy Labels)
3. The process should be possible for automation, in order to facilitate the iterative process of the development as well the exploration for improving the quality of the results.
4. The process should be able to adapt to what is provided by the PaL house (types of monitored data, installations etc.).

By looking through the possibilities and the constraints in the method review in Coakley et al. (2014), it is assumed that an optimization technique using physical parameters for the calibration could be appropriate for the above points. That is because these techniques are usually easy to automate as mentioned in the review, while the use of physical parameters (such as the U-values) renders the results of calibration comparable and directly usable for a prognostic BPS model. Also, a method like this can be possible extended or supported by intuitive choices from the designer that can limit the search space of the solution significantly (e.g. by ‘suspecting’ the range of values for a parameter and adding it to the calibration).

For the specific problem type the following techniques have been considered. The reason is different for each technique and is analysed per case below. Also, it has to be noted that an extensive research on the most optimal method for the process is out of the scope of this study, as it is mostly focusing in developing and testing the process for the PaL House case study.

- Genetic Algorithm
- Artificial Neural Networks
- Kalman filtering

A Genetic Algorithm can be shortly described as a problem solving method that uses relationships and concepts found in genetics and the Darwinian theory of evolution as inspiration for its modelling structure. It is described in Deepa (2008) as a search technique to find approximate solutions for optimization – search problems while the original formulation was proposed by Holland (1975). For the specific calibration problem, it is advantageous as its implementation can be relatively simple and add limited complexity in the whole process. Nevertheless, as mentioned in Deepa (2008) they can be somewhat slow to converge and they depend on many parameters that are usually configured by experience. Also, as they are stochastic by nature there is no guarantee that they will converge to one specific solution.

Nevertheless, they can find a plethora of suitable (enough) solutions. This point can be very useful as some of the problems typically found in BPS calibration are that an exact solution might not be unique or even not existing, as suggested by Carroll and Hitchcock (1993). According to the authors, the second is usually due to the incomplete representation of reality through the model, while the first depend on the defined minimization criteria.

The Artificial Neural Network (ANN) is a an information processing paradigm inspired by the structure of biological nervous systems, such as the network of neurons in the human brain (Morton, 1995). It is able to learn information patterns within a multidimensional domain, store them through connection rules (synaptic weights) and making it available for use with new data, even noisy one (Kalogirou and Bojic, 2000). It has been extensively used for building model calibration in many different studies such as the one above, usually as alternative for dynamic simulations which use large amount of input parameters. For the specific study, it can be applied with measured data to learn underlying non-linear relationships e.g. between the monitored temperature and physical properties. Nevertheless, the implementation and design of an effective network usually involves complicated architecture making the --rocess more difficult to follow and correct if needed. It is a “black box” technique, as is genetic algorithm but with the difference, that its way of modelling reality cannot be easily extended for a prognostic, physical model.

The Kalman filtering can be described as an optimal recursive data processing technique (Maybeck, 1979). It can be used to process data from various sources, even with heavy noise, and provide improved estimations of a target value by using a variety of methods, such as system knowledge, statistics etc. It is usually used in real time systems with a lot of sensors and noise such as in aircraft control or in water level estimation etc. For the specific study, it could be used to improve the quality of a model estimation using monitored data, especially when noise is included (e.g. for temperature estimation, noise might originate from natural ventilation or occupation behaviour). The use of such an algorithm would be very interesting for creating a real-time model that is improving constantly by using noisy monitored data, and thus capture the real conditions in the building. Nevertheless, for the targets of this study it is not considered appropriate for estimating parameter values by using a short period of monitored data.

By comparing the above methods the genetic algorithm is eventually selected. The simplicity, transparency and the ability to create readily a plethora of solutions are some of the main reason behind this choice. The process can be seen in the following diagram. In the middle the general process is shown while on the right an adaptation to the specific problem is performed.

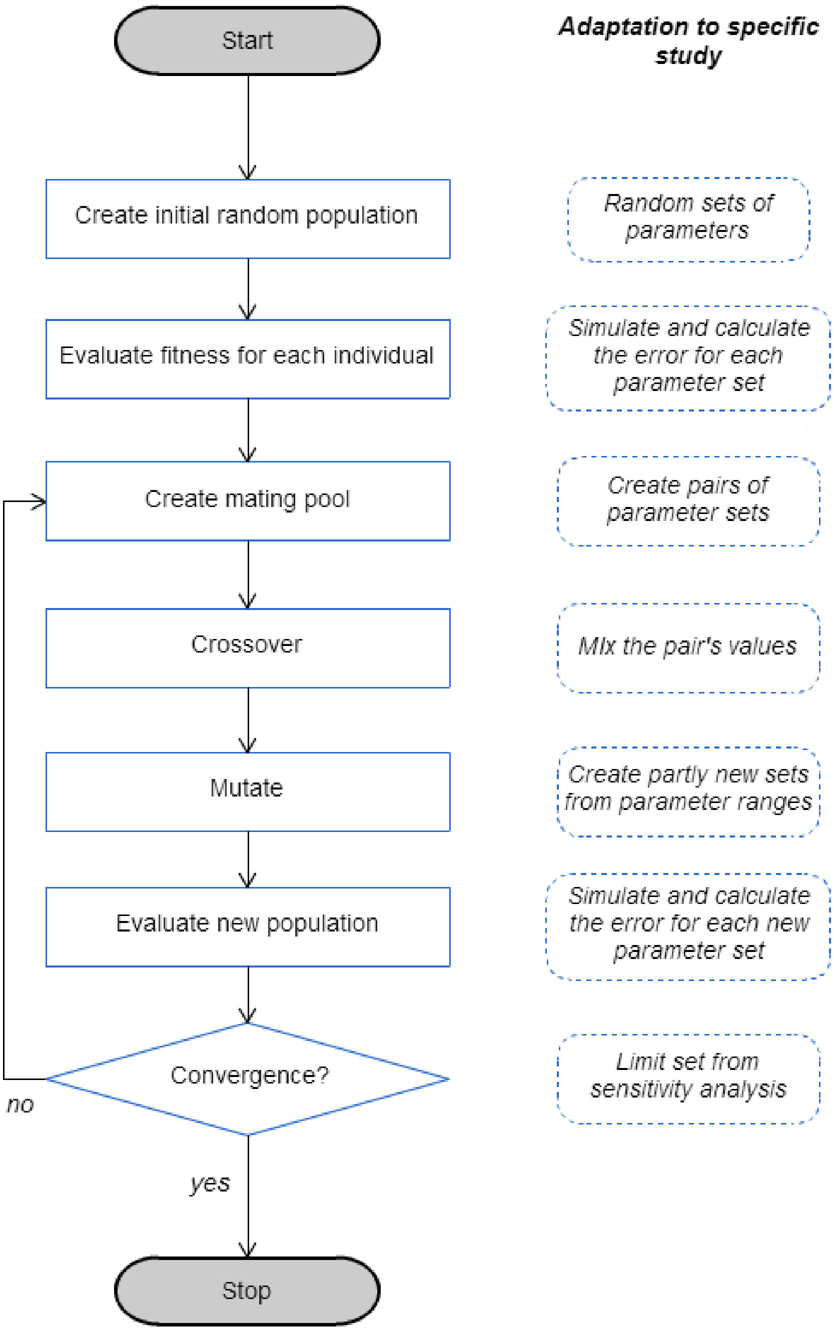


Fig. 16: Genetic algorithm process

3.4 Parameter selection

As discussed in the previous chapter, the following parameters are used in the model, shown with their abbreviations in brackets. It is noted the parameters controlling the crack infiltration in the EnergyPlus simulation are two, a coefficient and an exponent. Their significance on the specific case study will be investigated in the sensitivity analysis.

- *[cond]* Opaque envelope equivalent conductivity (W/m^2K)
- *[inf_coef]* Cracks flow coefficient ($m^3/s/m^2$)
- *[inf_exp]* Cracks flow exponent (from 0.5 to 1)
- *[trans]* U-value of transparent envelope (W/mK)
- *[solar]* Solar gains coefficient (from 0 to 1)

It can be observed that the thermal resistance of the opaque envelope is measured here in equivalent thermal conductivity while the one of the transparent envelope in combined U-value (glass and frame). Both measures are expressing the same property, but in the case of conductivity, this property refers to one material while for U-value on constructions – assemblies of different materials. The reason for this difference is that the input of the simulation program accepts these specific formats for the corresponding pars of the building envelope. Thus, for the opaque building envelope, which in reality is also a made from assemblies of different materials, the U-value of each assembly is transformed into an equivalent conductivity as if, e.g. a wall, was made by only one material.

Parameter detail level

In the following, the assumed detail level for the parameters is be discussed, i.e. if each of the elements of the house would assume a separate conductivity/U-value or one averaged value would be assumed for each parameter of the total building envelope.

For the U-values/conductivities of the elements, it is assumed that the relative importance between each other is mainly depending on the relationships between their areas. U-values affect directly the transmission heat losses, which in turn affect the temperature curve inside the house and thus the calibration. The general heat loss formula through a building element is (Linden, 2013):

$$Q_{trans} = U * A * \Delta T \quad \text{(Eq. 2)}$$

Where:

- Q is the transmission heat loss
- U is the U-value of the element (if it is uniform, otherwise, the combined U value of the assembly)
- A is the area of the element
- ΔT is the temperature difference between inside-outside.

If ΔT is assumed uniform for a zone, the U-value parameters of the different elements will have as weights their relevant areas. Therefore, for an element with an area ten time larger than another, the influence of the U-value will be proportional, as a change on it will affect the model much more than the same change on the other. Since the calibration uses an optimization algorithm which is based on minimization of error between temperature curves, it could be possibly assumed that the most influential U-values (for the elements with the largest areas) will be dominating the calibration algorithm.

On the other hand, if the U-values are weighted according to their areas to achieve uniform influence between them, then the algorithm could find fit solutions wherever the aggregation of U-values matches. For example if the U-value of one wall is 0.1 and the other is 0.2 and their influence on the calibration is the same, then the algorithm could find as a solution that both are 0.15 or their values are switched or in fact, every possible combination between them that equals 0.3. That is mainly the reason why it is avoided in this study to calibrate with separate U-value per wall. The combinations would be so many that it would be practically equivalent to use a lumped mass model.

Similarly, the same effect can be assumed with the with solar gain factors between the different windows and for the infiltration parameters between different zones.

Climate properties effect on calibration algorithm

From the space heat demand calculation formula in Chapter 2 it can be assumed that the effects of all the parameters examined in this study are aggregated to the total heat losses of the house (or space heat demand). These total heat losses are resulting to a specific temperature curve that is subsequently compared with the measured temperature curve. It can be then suggested that the optimization algorithm might not be able to reach a parameter set close to the actual but a set of random values, with the same aggregated effects on the temperature as the measured one. It is the generalization of the problem described before with the separate component U-values.

However for this case, the following assumption can be made to indicate that the algorithm would possible work.

As shown from the calculation formula of transmission heat losses, the U-value effect on the temperature is “connected” with a climatic parameter which in this case is the exterior-interior temperature difference. Similarly, all the parameters of this study have connected climatic properties, from the calculation formulas for their corresponding heat losses/gains (as derived by Linden (2013)). These connected climate parameters can be seen in the following table.

Model parameters	**Climate parameters**		
Opaque envelope equivalent conductivity	**ΔT** exterior – interior temperature difference		
Cracks flow coefficient *Cracks flow exponent*	**ΔT** temp difference	**ΔP** *pressure difference*	**u_{wind}** *wind speed*
U-value transparent envelope	**ΔT** Exterior – Interior temperature difference		
Solar gains coefficient	**I** solar irradiation		

Table 2: Connection of model parameters with climate properties

It can be thus assumed that the algorithm would be able to discern between the effects of the infiltration, solar gain and thermal properties as their heat transfer effects are all connected with different climatic parameters. For the thermal properties of opaque and transparent building envelope it is also assumed that the algorithm would be able to discern them, as usually the U-values of transparent elements are at least one order of magnitude larger than the ones of the opaque elements. Still some coupling would be observed, as with the infiltration parameters.

Indications for the validity of this assumption would be given in the validation of calibration process in Section 6.2. Nevertheless, a more detailed study on this effect is suggested.

3.5 Modelling methodology

The EnergyPlus simulation model of the house can be designed in the following two ways, based on the assignment of climatic zones in the interior space.

- Single-zone (lumped mass) model
- Multi-zone model

The real situation for the specific typology is usually between these two boundary situations, with rooms having similar but not entirely equal temperatures, envelope properties etc.

Single-zone model

The simplest way to model the house would be to assume that all rooms belong in the same zone. This argument can be viable if the air transfer between the rooms is unobstructed, the interior walls are uninsulated and if there is everywhere similar activity and HVAC. Moreover, this modelling method can provide a significant simplification in the process. If the result difference between the multi and single zone modelling is not large, then it could be assumed that for similar houses and conditions one validation point/sensor is enough.

On the other hand, with a single-zone calibration it is harder to indicate differences between the thermal properties of the building elements. In that case it is assumed that many parameter combinations could provide the same data fitting, thus making it difficult to provide estimations for each element separately, as shown in the section above. For the case study, it is noted that there can be 12 different parameters representing the different panel/elements of the house, thus the number of their possible combinations can be very large. Therefore, it would make more sense to lump all the U-values and the different infiltrations to total house values and calibrate the model with only these two parameters. This would minimize the search space, possibly increasing the accuracy of the calibration.

This modelling provides insight on the total efficiency of the building envelope. Furthermore, the aggregation is also used for the Energy Label methodology and thus it would be possible to compare with it. The method can provide an answer on the second research question about the old houses. Since these are labelled by assuming U-values and infiltration rates based on their year of construction etc., a single zone calibration can be used to find values that are closer to the real situation. The process is also illustrated in the next diagram.

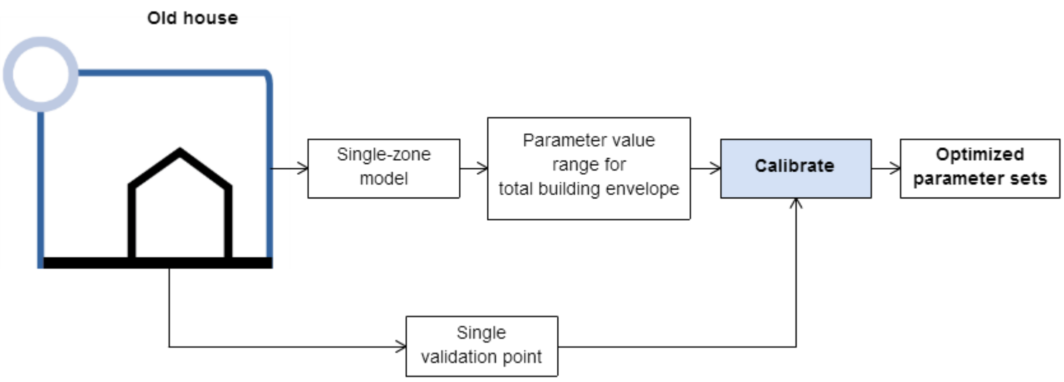


Fig. 17: Calibration process for old houses

The same method can be applied in the case of new houses to verify the total efficiency of the building envelope. Also, it might be interesting to compare between a single and multi-zone model of the same design values to investigate which of the two ways of modelling is closer to the real situation.

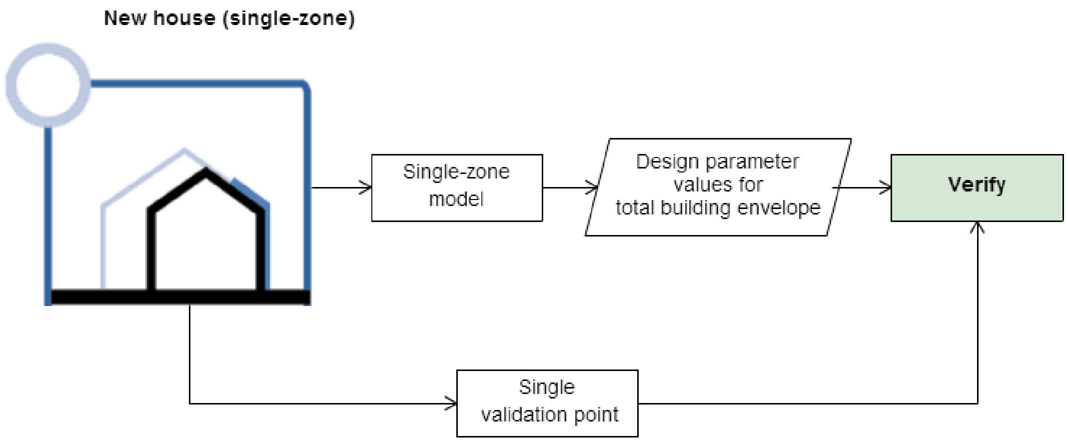


Fig. 18: Single zone process for new houses

Multi-zone model

An additional level of detail can be provided for the new houses as the design targets for the U-values of each component are available. In reality these values can still vary from their designed counterparts due to construction inaccuracies etc. Thus, for the new houses it would be also interesting to see if the data fitting would be almost perfect when the exact design values are used in the model.

For this, a non-lumped model have to be used, where each surface is represented with a separate U value. To allow more accuracy in the verification, it would be useful to provide additional validation points. That is because, if there is only one validation point e.g. in the living room, the verification of the design U-values in the bedroom on the top floor etc. would be difficult. Since for the case study there are measured data available for each room/zone, it is possible to simulate the house with a multi-zone model and check the error in all zones. Thus the first research question can be answered also by a multi-zone verification of the model as illustrated below.

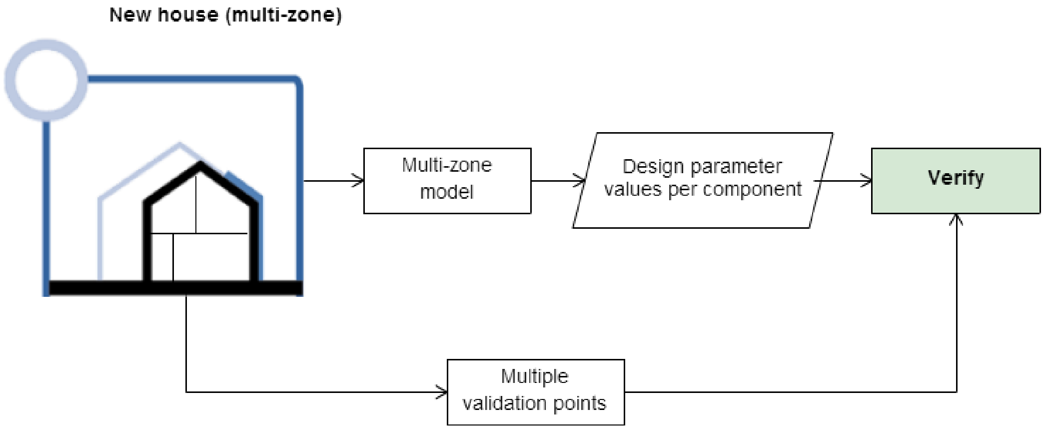


Fig. 19: Multi zone process for new houses

3.6 Sensitivity analysis method

As mentioned in many studies on calibration methods (Coakley et al., 2014), a usual first target is to get an insight on the influence of the different parameters on the data fitting process. For example, in order to identify strong and weak parameters, Reddy et al. (2007) propose in their methodology a coarse search on the parameter space by a Monte-Carlo simulation approach and other sensitivity analysis techniques. This allows them to use static values for the weak and specify narrower ranges for the strong parameters, in order to further refine the search space. Another recent research, relevant to the current study, is using an extensive Monte Carlo analysis to identify the influence of factors relevant to energy consumption and comfort in a reference residential building (Ioannou and Itard, 2015). In the same study, the techniques are presented as grouped in three classes, depending on how many parameters are changing in the same analysis, if the evaluation is based on extreme values or a range etc.

The three classes are:

- screening methods
- local sensitivity methods
- global sensitivity methods.

Following the trend in the relevant studies and in order to get a quantifiable 'feel' on the parameters, a sensitivity analysis is also suggested here. Due to the premises set in the rest of the chapter, a local sensitivity analysis is chosen. According to Ioannou and Itard (2015) it is based on the OAT approach (one-parameter-at-a-time) and the evaluation of output variability is based on the variation of the parameter between a range of values. It is further mentioned, that the method is useful in comparing the relative importance of parameters, which is indeed the goal of the sensitivity analysis in this study. However, the method assumes that the input-output relationship is linear while the effect of the parameters is considered independent from each other. Unfortunately these assumptions are not valid for the specific problem, as the parameters are interconnected (e.g. due to the effect of each other on the ΔT) and their input-output cannot be guaranteed as linear in their value range. Nevertheless, they can still offer some insight for the specific case of PaL House, assuming that the designed and actual parameter set is not far from each other. Therefore, while one parameter is varying the others are assuming their design values, leading presumable to a minimum effect coupling, while their ranges are kept to realistic values for a building with very efficient envelope.

3.7 Validation methodology

By taking into account what is included in the above methodology, the validation is designed accordingly. It is divided into two types:

1. Validation of the calibration process itself
2. Validation of the calibration results of the PaL house

The reason for this differentiation is to first witness if the calibration process works by trying to find some known sets of parameters. This is something that cannot be achieved with the measured data from the PaL house, as the set of parameters that instigate the real house behaviour is considered unknown, for the reasons described in the previous. Therefore, it is apparent to disengage the measured data needed for the calibration from the uncertainty of the real situation.

One method to achieve this is to create ad-hoc "measured data" by model simulation, using a known set of parameters. Then, the calibration process can be used on an un-set simulation model to try to find these parameters, making possible the evaluation of the effectiveness of the algorithm alone on finding the known solution. In this way, the measured data are also clean from any noise, allowing the possibility of a "perfect" match from the algorithm.

After the calibration process, the validation on the real measured data of the PaL house takes place. This can be performed by using different datasets for learning and verification, with various ratios and characteristics between them. Thus, the calibration can results to some parameters by minimizing the error based on the learning dataset and then with these parameters, check if similar error is produced in the verification dataset. Datasets of various durations, seasons and weather conditions are used to increase the quality of the validation.

3.8 Software development methodology

The development methodology that is used is based partially on the concepts of Agile Development and Extreme Programming (XP) (Warden, 2008). The latter is an alternative to the typical sequential development circle of analysis, design, coding and testing.

In general, these methodologies include a large base of concepts and practices, mostly suitable for teams of developers. Nevertheless, the following practices can be adapted for use for this research:

- Short development circle, usually a week long
- Fast implementation of initial working prototype
- Use of a version control system
- Use of domain experts and customers for defining features through documented user stories
- Fast implementation of changing requirements

An important clarification for the above, especially due to the challenging subject of the thesis, is that a tool with the minimum viable (core) characteristics is developed initially. The changing requirements and the extra features that are expected in such a project would be then more easily implemented and tested in further consequent steps.

Finally, after an initial research, the programming language **Python (v. 2.7)** is mainly used to develop the different components for the process and optimization tool. Some possibly reasons behind this decision are the following:

- Easy to learn and to program in a fast and efficient way
- Appropriate for the processes involved in the thesis
- Extensive libraries for developing the wide range of these components. Some of the most used libraries are the following:
    - **Numpy, Scipy**: for extending the python functionality for scientific use (NumPy Developers, 2013) (Scipy)
    - **Pandas**: for data analysis (PyData Development Team, 2015)
    - **Database SDK** (Software Development Kit): for interacting with the used databases. (TempoIQ, 2015)
    - **Eppy**: for manipulating easily the input files of EnergyPlus (Santosh, 2015)
    - **DEAP:** evolutionary algorithm library (De Rainville, 2014)

4. Experiment setup

In the following chapter the parameters and the most important details for the process setup are presented. Namely these are the data granularity. The measured data filtering method, the parameter values from the design documentation, the metrics used and the configuration of the genetic algorithm used for calibration. Extensive details on further aspects of the experiment, such as how the monitored data is selected, how the simulation data is produced, how they are pre- and post-processed and how the whole process is automated, can be found in the appendices 9.2 and 9.3.

4.1 Data granularity

The data frequency for the different measured sources are given below:

- The KNMI weather database API can output hourly and daily data
- The monitoring database API can output interpolations of different periods. Essentially the sensor data frequency depends on their activation. In night, without changes in light intensity and significant changes in temperature, the frequency might be quite long. Therefore, if sensor malfunctioning periods are excluded, their values can be safely interpolated.
- The simulation can output data in the same frequency as the given weather file

Therefore, the hourly interpolation is chosen for the granularity of data. The reasoning behind it is that since the main research objective is based on finding the optimal physical characteristics of the house to fit the curves of measured and simulations (and especially their rates of temperature change), a high sampling is not helping the results. On the contrary a mean value is needed for the hourly period, as the main interfering factors have already been excluded by data filtering.

More details on the sensors and the weather data creation can be found in the appendices.

4.2 Measured data filtering

The rooms with temperature sensors inside the house are the following:

- Living room
- Bedroom
- Study room
- Bathroom
- Corridor (front door hall)

For the reasons discussed in the problem statement, Chapter 2, the data coming from these sensors is filtered to acquire the periods that the house is on free-run (no interference). The data filtering along with the acceptable levels are the following:

- 1st filtering -> main sensor malfunction -> None
- 2nd filtering -> occupation -> None
- 3rd filtering -> energy use -> 0.8 Watt (it is considered base load)
- 4th filtering -> ventilation -> None

Malfunction is considered to be a period without broadcasting for more than 12 hours. Earlier than that, it is considered that the sensor is not sending new data because of stability of the condition inside the house. This can be seen happening mainly in the night where light intensity is not changing. Also it can be mentioned that the sensors sensitivity only to temperature is about 0.10 - 0.20 °C.

For the single-zone calibration and verification, only the living room sensor is used to represent the average conditions in the house. It is exactly in the centre of the theoretical aggregated zone of the house, in comparison with the other sensors that are in the corners of rooms. Also, the total volume of the living room is almost 70% of the house volume For the multi-zone verification, all the main sensors are taken into account. Therefore, the available periods are less, due to malfunction periods on the sensors.

By applying the above data filtering the following available periods are found from 1st October 2014 to 10th May 2015.

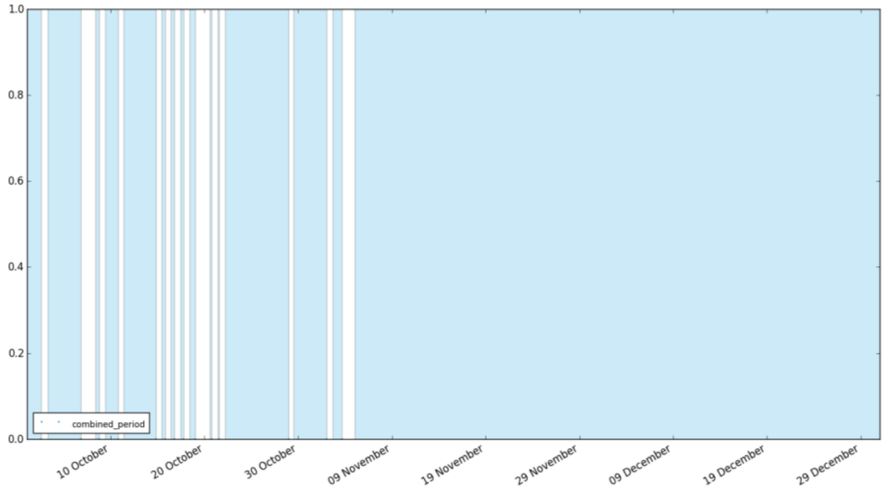


Fig. 20: Filtered periods for 2014 (white periods are selected)

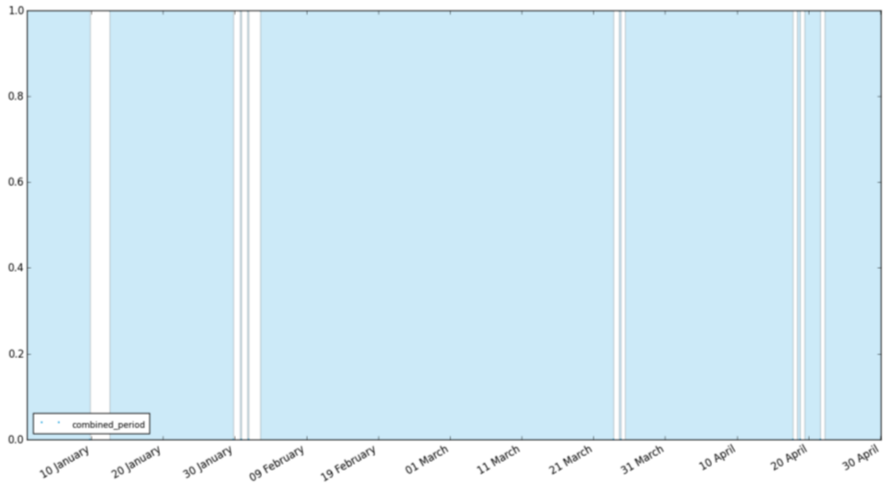


Fig. 21: Filtered periods for 2015 (white periods are selected)

It can be observed that available periods make only a small portion of the total monitored time. This is accounted to the extensive exhibition use of the house as well as the use of heating, ventilation etc. Also most of the individual periods are a bit more than a day, with some notable exceptions such as the around 6 day period of January. This is expected as the most typical period that the house remained in steady state was the night.

This difference can possibly have an effect on the calibration quality as well the fact that mostly the night hours are used. Nevertheless, this effect can be studied only on a limited basis due to the amount of data. Specifically, the effect of calibrating with the 6-day period–almost a continuous week–will be observed more closely in comparison with the rest. A statistical analysis of the available periods can be found in the next tables.

Statistical analysis - single-zone model	
Number of periods	23
Max duration (days)	2.75
Min duration (days)	0.50
Average (days)	0.87
Standard Deviation (days)	0.52

Table 3: Statistical analysis of the filtered periods for the single-zone model (in days)

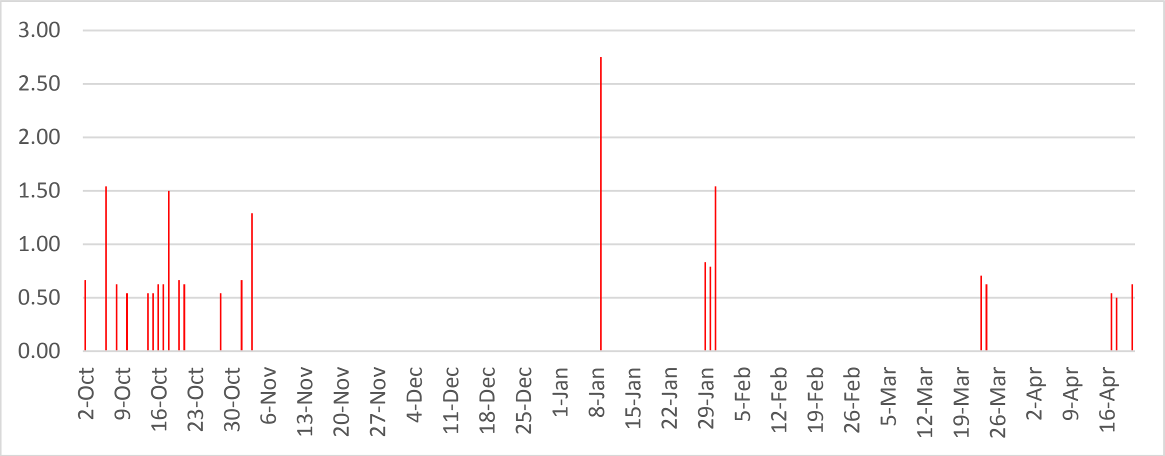


Fig. 22: Distribution and size (in days) of filtered periods for single-zone model

Statistical analysis - multi-zone model	
Number of periods	19
Max duration (days)	2.75
Min duration (days)	0.54
Average (days)	0.89
Standard Deviation (days)	0.55

Table 4: Statistical analysis of the filtered periods for the multi-zone model (in days)

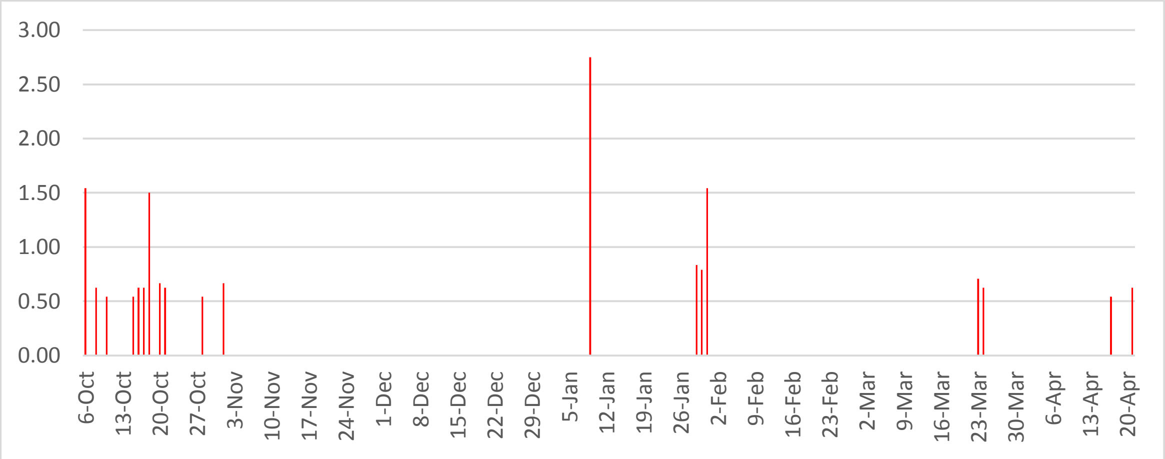


Fig. 23: Distribution and size (in days) of filtered periods for multi-zone model

Use case scenarios

The above multiple period case with an average duration between 12-24 hours can be assumed as a result of the scenario of using the process in a house with the tenants present. Ideally, the free-run performance of the building envelope should be researched with no interference from the users, no internal loads, opening windows etc. Nevertheless, it can be suggested that this use case of the process is only realistic when all tenants are not present in the house e.g. they are on vacations. However, even with the case of tenants being present when the monitoring is taking place, periods with limited interference can still be used. These could be the night-time or the time that all tenants are on their work/school etc.

The calibration process with known parameters is validated in Chapter 6 for both scenarios. However, the validation of the case study with real measured data will be done for the scenario of multiple durations, due to the aforementioned limited availability from the PaL House and the small maximum duration of measurements (2.75 days).

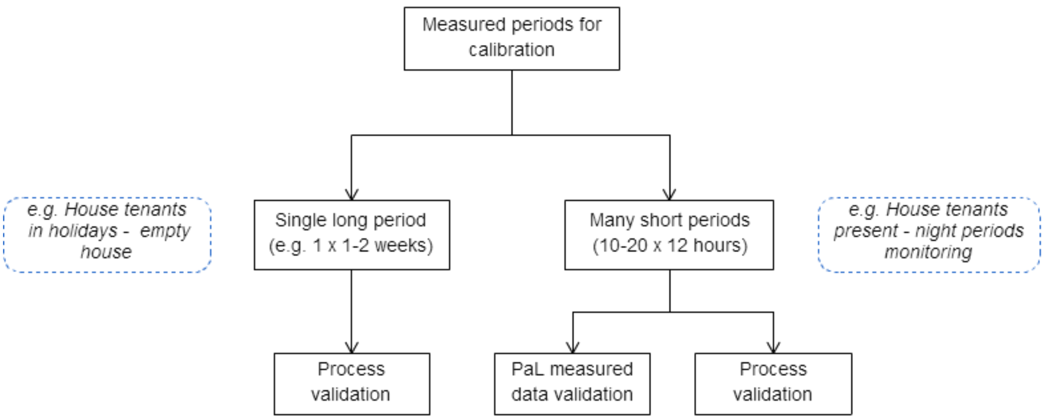


Fig. 24: Monitoring duration for process use-case scenarios (with validations performed in this study)

4.3 Design model parameter set

Below the design parameters of the Pal House are presented, as taken by the documentation or calculated here.

Opaque envelope conductivity

From the as-built construction documentation of the Pal House (Pret-a-loger, 2014), the U-values of the components are extracted. These are calculated from the known layers that comprise the components, their nominal thicknesses and the material properties found in the products' specifications. Subsequently, from these U-values, the equivalent conductivities are calculated. More details on this can be found in Section 9.4 in the appendix. The naming convention below is used for the EnergyPlus model to assist the query from the algorithm. The conductivities start with PaLC, then the next part signifies the element (F = floor, R = roof, We = external wall, Wi = interior wall) and the last part the position of the element (f = first floor, g = ground floor, 0e= ground floor - east, 0110 = ground floor with a thickness of 110mm etc.).

- PalCFf = 0.248 W/m^{2}K
- PalCFg = 0.037 W/m^{2}K

- PalCRn = 0.034 W/m^{2}K
- PalCRs = 0.038 W/m^{2}K

- PalCWe0e = 0.042 W/m^{2}K
- PalCWe0n = 0.040 W/m^{2}K
- PalCWe0s = 0.041 W/m^{2}K
- PalCWe0w = 0.042 W/m^{2}K
-
- PalCWe1e = 0.042 W/m^{2}K
- PalCWe1n = 0.040 W/m^{2}K
- PalCWe1s = 0.041 W/m^{2}K
- PalCWe1w = 0.042 W/m^{2}K

- PalCWi0110 = 0.125 W/m^{2}K
- PalCWi0150 = 0.171 W/m^{2}K
- PalCWi1110 = 0.125 W/m^{2}K
- PalCWi1150 = 0.171 W/m^{2}K

From the roof, ground floor and external wall parameters, a weighted average equivalent conductivity for the house is derived, using areas as weights. It is calculated as **cond = 0.039 W/m^{2}K.**

Infiltration rate parameters

The infiltration rate parameters are calculated in design documentation following the intention of the designers and the constructor for passive house standard. This standard suggests an infiltration rate of n50 = 0.6 ach.

The volume of the building is V = 227.99 m^3, therefore the m^3 per s value is:

$n_{50} = 0.6ach \iff q_{v50} = 227.99*0.6/60*60 \iff q_{v50} = 0.038m^3/s$

By taking an average value of exponent to 0.70, the infiltration heat loss formula yields:

$Q_v = C\ DP^{0.7} \iff C = Q_v / DP^{0.7} \iff C = 0.0024575\ m^3/s$

The rate divided per m^2 of exposed building area (316 m^2 for this house) yields:

$C = 1.0\ E\text{-}05\ m^{3/}s/m^2$

Therefore the parameters are **inf_coef = 1.0 E-05 $m^3/s/m^2$** and **inf_exp = 0.70**

U-value of transparent envelope and solar gains coefficient

For all the windows in the house the following glass and frame models are used. Their U-values are derived from the documentation of the manufacturer:

- Laminated K glass N HR++ - 332*-13-442*
  - ➔ U_g = 1.113 W/mK (ISO 10292/ EN 673)

- Schuco CT-70 Corona - PVC frame
  - ➔ U_f = 1.3 W/mK

Therefore the average U-value for all the windows (U_w) of the house is calculated as **trans = 1.3 W/mK**

From the documentation and due to the fact that energy glass is used, the solar gain coefficient is taken as **solar = 0.4**.

4.4 Metrics for simulation-measurement difference

The most usual metrics for building performance calibration are used, as derived from Coakley et al. (2014). These are the following:

Mean Bias Error (MBE) (%)

It is a non-dimensional bias measure (i.e. sum of errors) between measured and simulated data for each hour. The MBE can provide an indication of the overall bias in the model and it captures the mean difference between measured and simulated data points. However, it can suffer from the cancelation effect where positive bias compensates for negative bias.

$$\text{MBE}\ (\%) = \frac{\sum_{i=1}^{N_p}(m_i - s_i)}{\sum_{i=1}^{N_p}(m_i)}$$

(Eq. 3) MBE

Root Mean Square Error (RMSE):

The root mean square error is a measure of the variability of the data and it is measured on the data unit.

$$\sqrt{\left(\sum_{i=1}^{N_p}(m_i - s_i)^2 / N_p\right)}$$

(Eq. 4): RMSE error

Coefficient of Variation of Root Mean Square Error CV(RMSE) (%):

This index allows one to determine how well a model fits the data by capturing offsetting errors between measured and simulated data. It does not suffer from the cancellation effect.

$$\text{CV RMSE}\ (\%) = \frac{\sqrt{\left(\sum_{i=1}^{N_p}(m_i - s_i)^2 / N_p\right)}}{\overline{m}}$$

(Eq. 5): CV(RMSE)

It is also mentioned that the limits for this convergence are based to the predicted energy consumption and are taken from standards such as the ASHRAE Guideline 14. Since temperature is used here as validation parameter, custom limits of these convergence are defined in the sensitivity analysis.

For the calibration fitness the **CV(RMSE) is used in order to avoid the cancellation effect.**

4.5 Genetic algorithm configuration

The configuration of the genetic algorithm used for calibration is defined in a first level by the way the calibration problem is modelled in the algorithm. Then, through a trial and error method, by running the algorithm and plotting the convergence diagrams, parameters can be fine-tuned or different operators used (e.g. crossover through ranking etc.).

- Number of generations: Stop when calibration target is succeed
- Population: 80 individuals
- Selection type: Tournament
- Crossover type: Uniform
- Mutation: Uniform Integer
- Elitism: used
- Crossover probability: 0.5
- Independent crossover probability: 0.5
- Mutation probability: 0.1
- Independent mutation probability: 0.8

Parameter search space

The search space of each parameter is based on realistic value ranges for the usual built environment. It is presented below in the form of min, max and interval.

	cond (W/m^{2}K)	inf_coef (m^3/s/m^2)	Inf_exp	trans (W/mK)	solar
MIN	0.025	1.0 E-05	0.50	0.60	0.01
MAX	0.350	200.0 E-05	1.00	6.00	0.80
INT	0.001	1.0 E-05	0.01	0.02	0.01

Table 5: Parameter search space

5. Results

In the following chapter, the results of the developed processes are presented. These include a sensitivity analysis, performed firstly on the effect of the measured data duration to the error size and secondly on the various effects of the parameters to the model. Then, a verification of the original design is conducted, by comparing measured data with a simulation configured with design values. Finally, the results of the calibration of a Pal House simulation for various measured periods are shown.

5.1 Sensitivity analysis

A sensitivity analysis is used on two aspects of the process. First, on the size of the measured period used for verification or calibration, as it is suspected it is affecting the range of the error found. Secondly, on the building envelope parameters, in order to find their relative importance to the error.

Measured period size effect study

The size effect is studied by showing a collection of temperature plots for different periods. These are 12 hours, 1 day, 2 days, 4 days, 7 days, 14 days, 21 days and a month. The periods are starting in the same day, 23 November 2014 as it was noted that the climatic conditions around this period include large temperature differences and fluctuations. Due to the shortage of large measured data durations, the data will be created by a simulation and assumed as measured. The parameters used for this simulation will assume their nominal design values, as they are not very far from reality, as shown in the verification before.

In order also to stress the effect of distance of the simulated with the measured parameters, two experiments are created. In the first the difference is small, the opaque building envelope conductivity is taken as 0.050 W/mK instead of 0.039 W/mK in the measured. In the second the difference is very large, with the same parameter taken as 0.35 W/mK. The result of this study is to provide a possible indication of how much data is needed to “create” enough error in order to for the calibration/verification to be effective. If e.g. the error is very small for a duration, then the calibration might not be able to get enough information out of it for finding the right combination of parameters.

Small difference in cond (example parameter)

- cond_measured = 0.039 W/m^{2}K
- cond_simulated = 0.050 W/m^{2}K

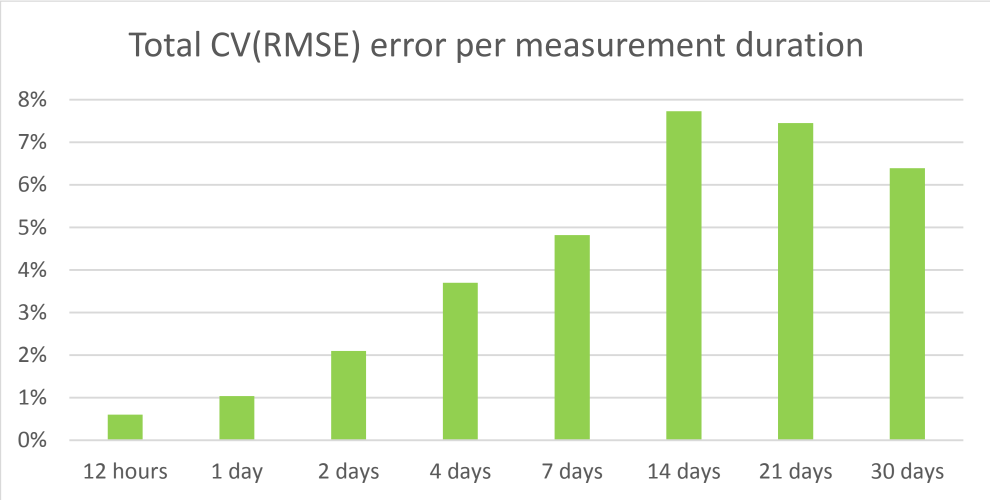
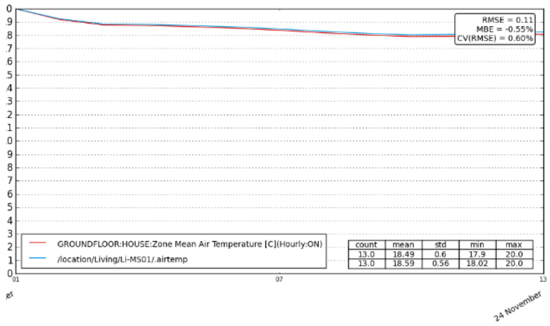
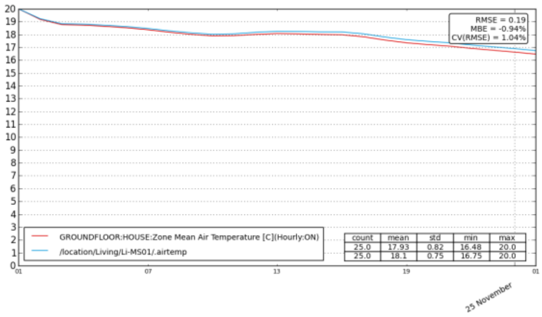
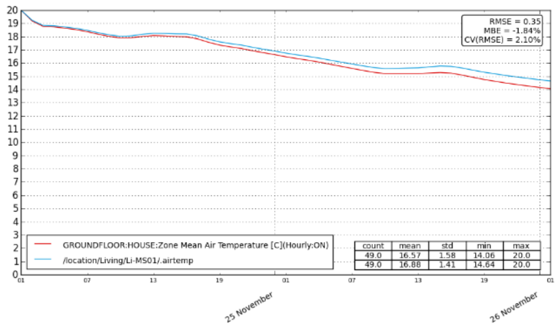
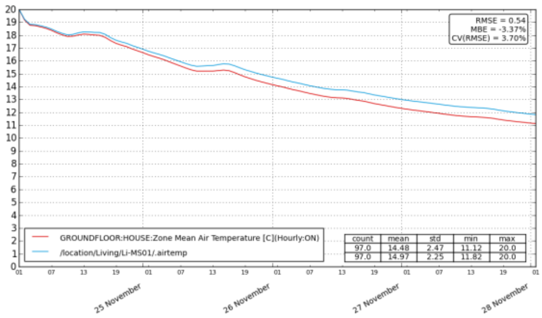


Table 6: Error per measurement duration – small parameter difference (measurement size sensitivity)









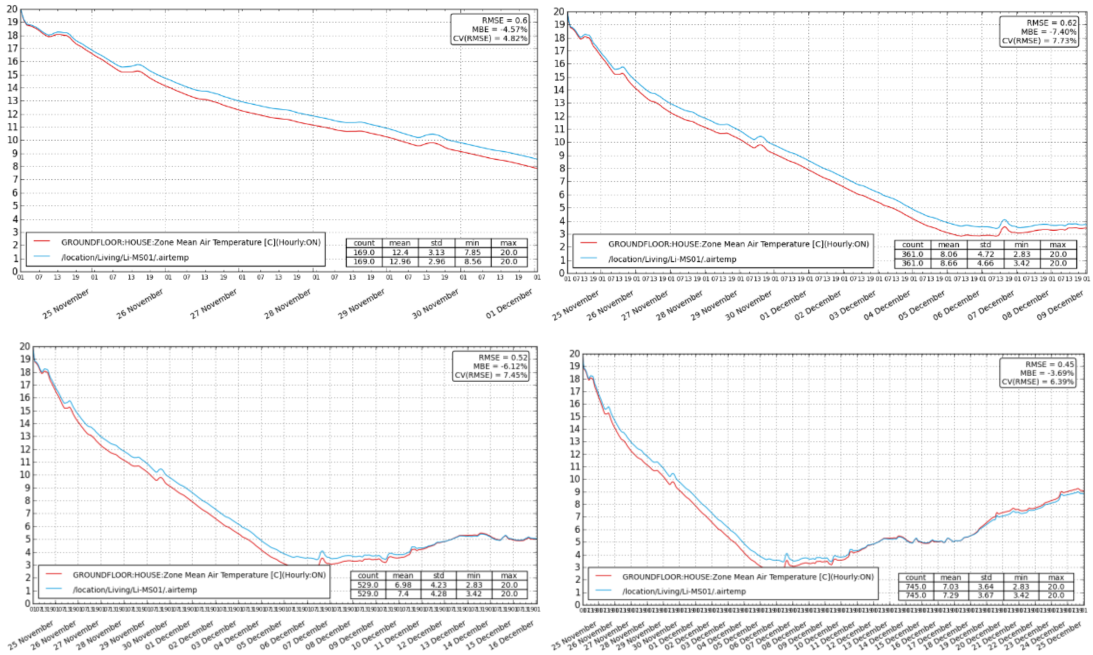


Fig. 25: Temperature plots for different durations (small difference). From top left towards down and right are for 12 hours, 1 day, 2 days, 4 days, 7 days, 14 days, 21 days and a month.

Large difference in cond (example parameter)

- cond_measured = 0.039 W/m^{2}K
- cond_simulated = 0.350 W/m^{2}K

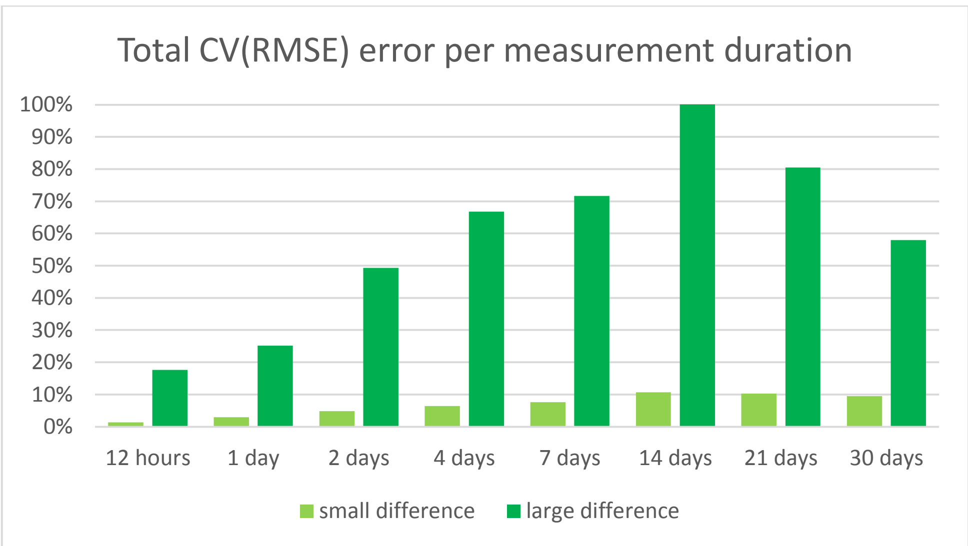


Table 7: Error per duration – large and small parameter difference (measurements size sensitivity)

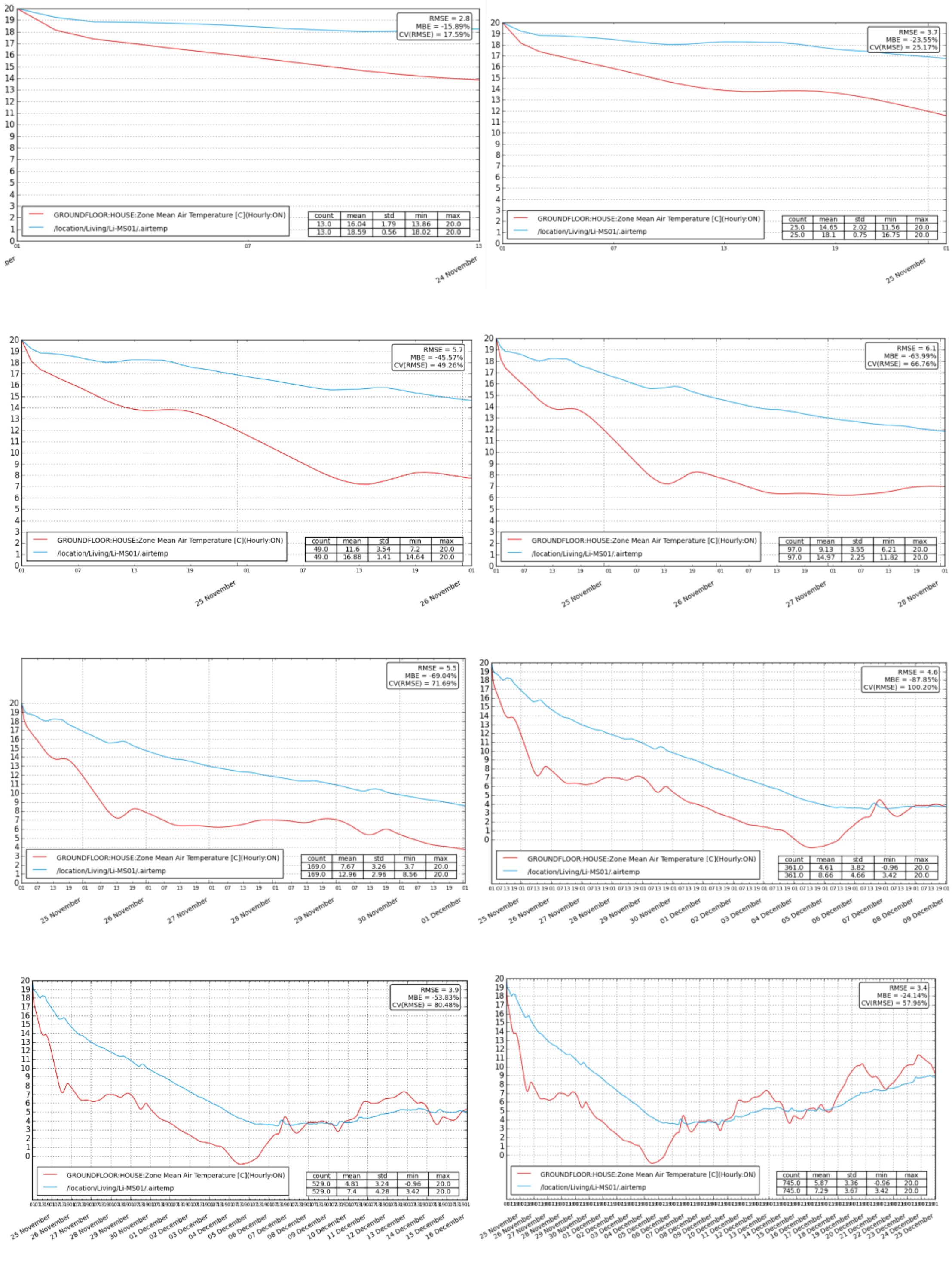


Fig. 26 Temperature plots for different durations (large difference). From top left towards down and right are for 12 hours, 1 day, 2 days, 4 days, 7 days, 14 days, 21 days and a month.

From the temperature plots above, there is an indication that for a free run period (no heating, no internal load) even if the measured and simulation data are not having the same parameters, their resulting interior temperature will follow the exterior temperature. For the small difference diagrams, it can be seen that the error is starting to grow slowly in the beginning until around the 14th day and then is diminishing till the end of the month. For the large difference, the error grows rapidly from the very first hours till again the 14th day where starts diminishing. Nevertheless, as it can be seen from the yearly diagram, the simulation curve is not following closely the measured curve after the 14th day but rather fluctuates around it. That is somewhat expected due to the existence of the glasshouse, as such large conductivity means that the heat created in the glasshouse can be directly transferred inside the house (and subsequently lost in a colder cloudy day).

From the total error figures it can be seen that the range in the small difference diagrams is around 0.5 to 8% while for the large difference diagrams starts on 20% and can reach even 100%. That suggests that when the difference between the measured and simulated parameters is becoming smaller, larger durations are needed in order to be able to have enough error for the calibration to work.

Sensitivity analysis results – Design values

In order to provide a more quantitative image of the impact of the different parameters, a sensitivity analysis is introduced for them. Inheriting from the base analysis component, the process is creating comparison metrics for different values of a parameter, showing how its variation affects the variation of the error and the corresponding energy losses. As mentioned above, a one-at-a-time (OAT) method will be used, where the target parameter will fluctuate over its search space range while the others remain constant.

Nevertheless, as expected by the building physics background of the heat loss calculation, the values of the static parameters can affect the fluctuation of the tested parameter. For example, a high static infiltration rate can limit the effect of the conductivity fluctuation, as the temperature difference between exterior and interior would be already rather small. On the contrary, a low infiltration rate would suggest that this difference would be higher and therefore the conductivity fluctuation will lead to more varying error and energy results. This coupling effect will be commented further on. The results of the sensitivity analysis are presented in the form of heat loss and error diagrams with the fluctuating parameter given in the title. The heat loss diagrams are shown analytically in the appendices on Section 9.5. The results are gathered and commented on the total sensitivity analysis section.

Opaque envelope equivalent conductivity [cond]

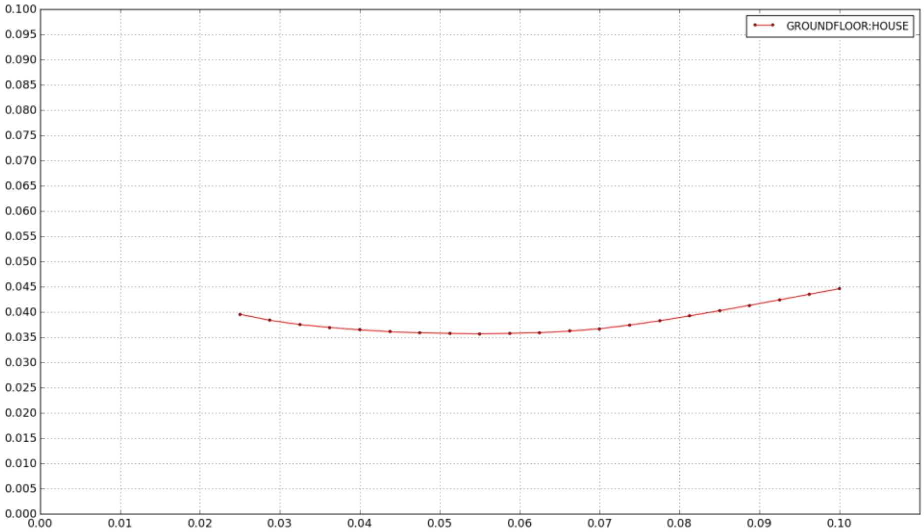


Fig. 27: Error diagram for fluctuating opaque envelope equivalent conductivity (W/m^{2}K)

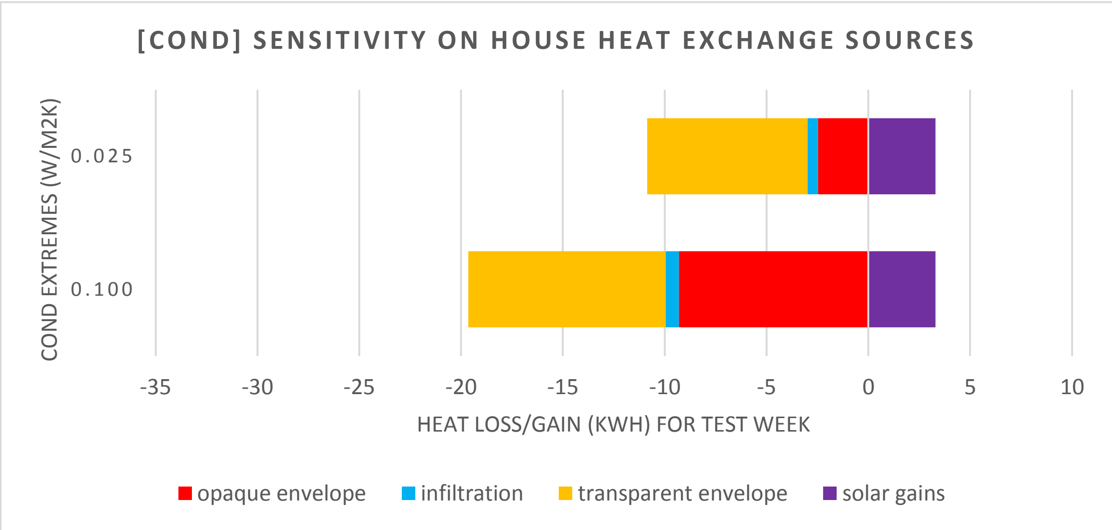


Fig. 28: Heat loss/gain with [cond] fluctuation

The effect on error is quite small, for the typical thermal conductivity range of a house with almost passive house values. Translated on energy it is more important, possibly due to the size of the envelope versus the volume it covers. An indication on the thermal conductivity is observed on the range of 0.04-0.06. A coupling can be observed with the U-values of the transparent envelope and lesser with the infiltration. This can be expected, as the faster temperature drop on high conductivities limits the conductive heat losses through the transparent elements. The lesser effect on infiltration can be accounted on the extra relation of the parameter with pressure and wind.

Infiltration flow coefficient [inf_coef]

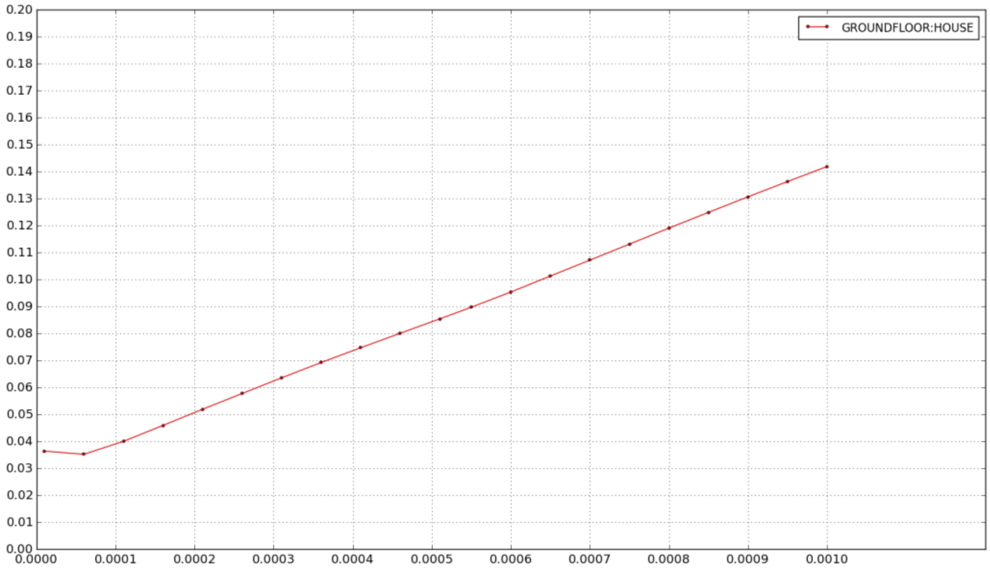


Fig. 29: Error diagram for fluctuating infiltration flow coef. ($m^3/s/m^2$)

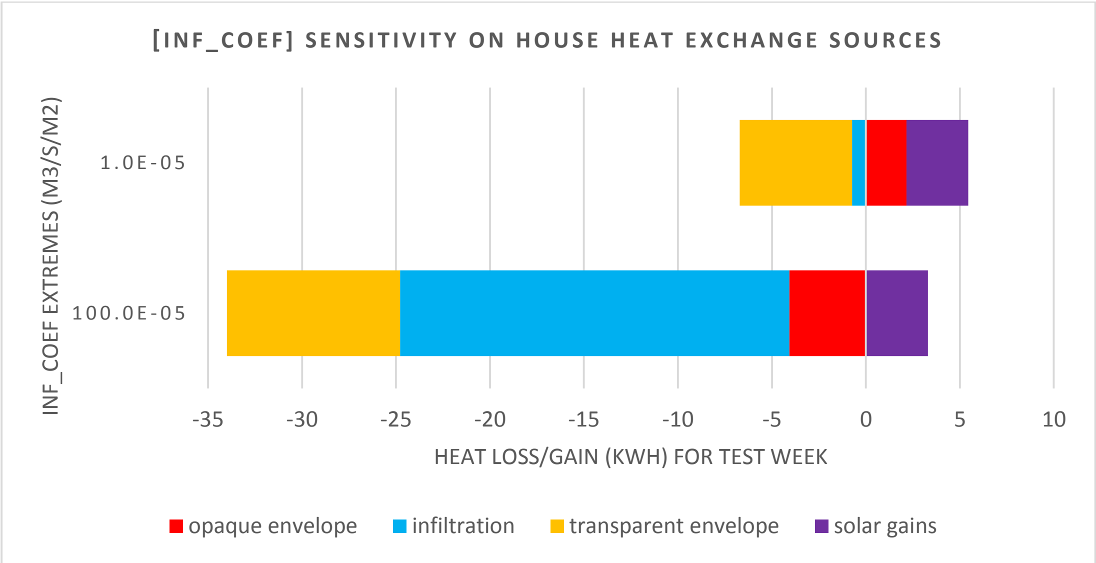


Fig 30: Heat loss/gain with [inf_coef] fluctuation

On the contrary, the effect on error is much higher for the infiltration flow, with almost 10% difference for the range boundaries. From the error plot, a range estimation for the house infiltration can be around 1 E-05 to 1 E-04. Energy effect is also high from almost 0 to 20 kWh, with coupling effects on both opaque conductivity and transparent U-value, again explained possible due to the drop of temperature inside the house.

Infiltration flow exponent [inf_exp]

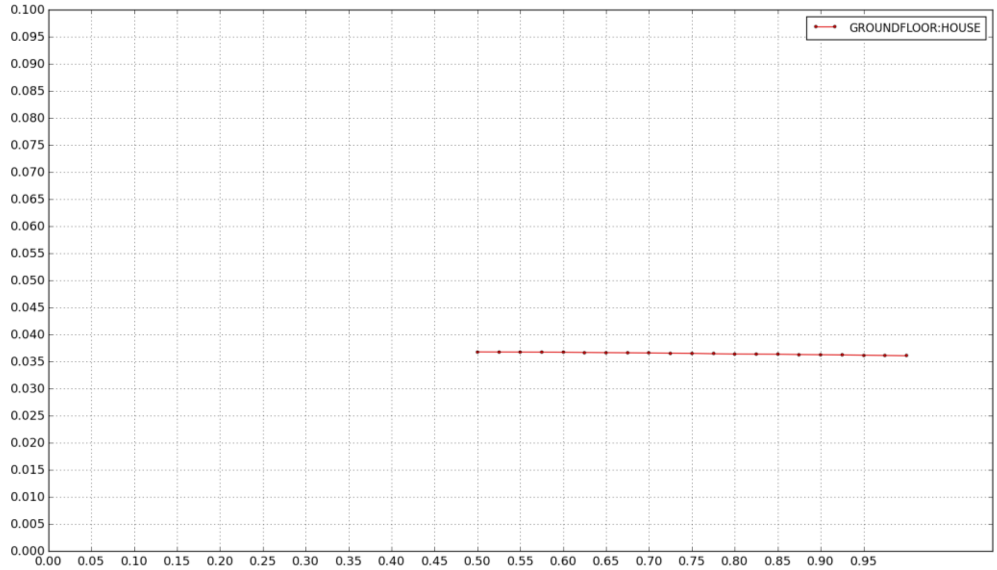


Fig. 31 Error diagram for fluctuating infiltration flow exponent

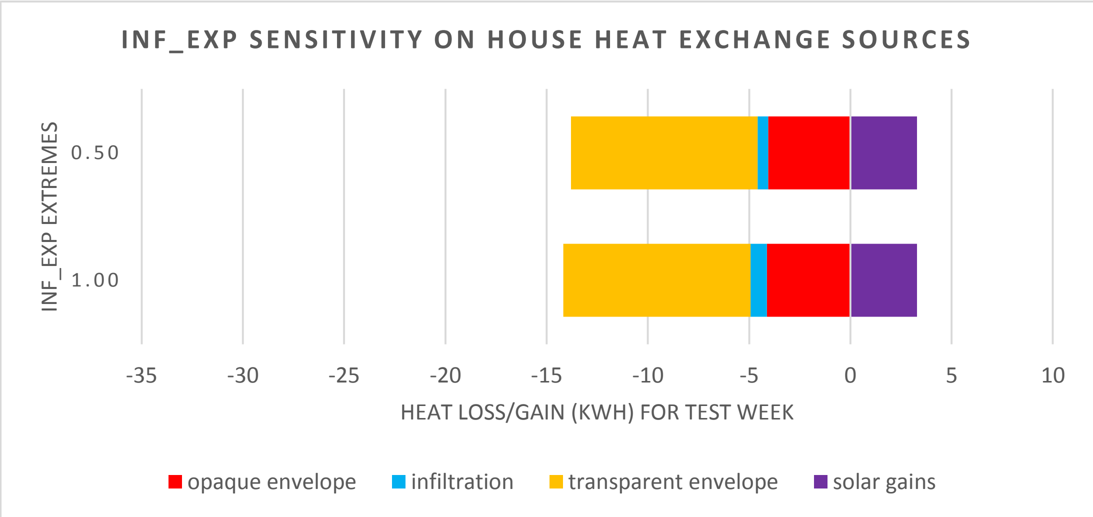


Fig 32: Heat loss/gain with [inf_exp] fluctuation

For the whole infiltration flow exponent range, the effect on the error and energy is almost null. Therefore, it is not useful to add it as a parameter to calibrate, as it is not providing a possibility to converge. If it was added, then its resulting value would be random, since the effect on the error and thus on the algorithm fitness would be minimal.

Transparent envelope U-value [trans]

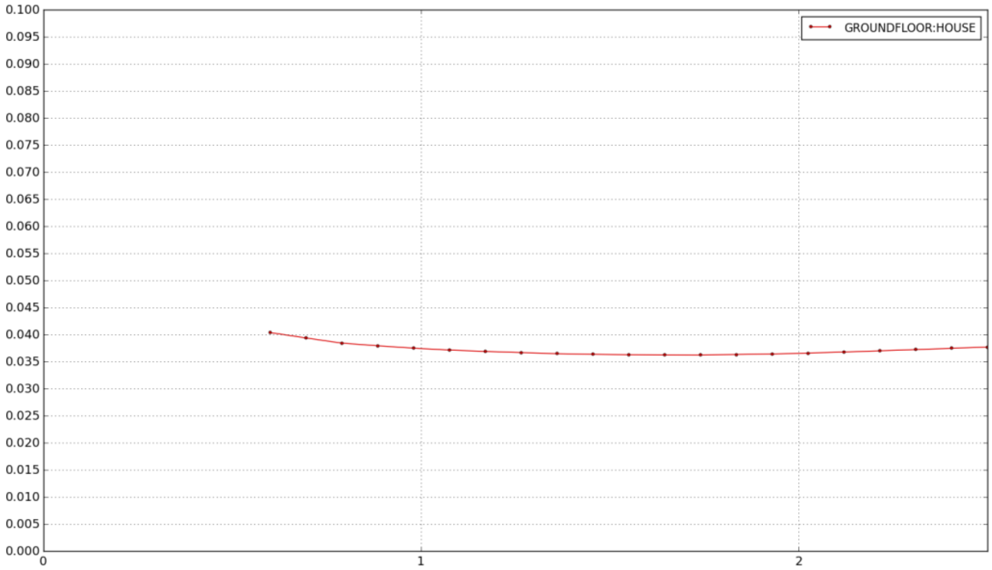


Fig. 33 Error diagram for fluctuating transparent envelope U-value (W/mK)

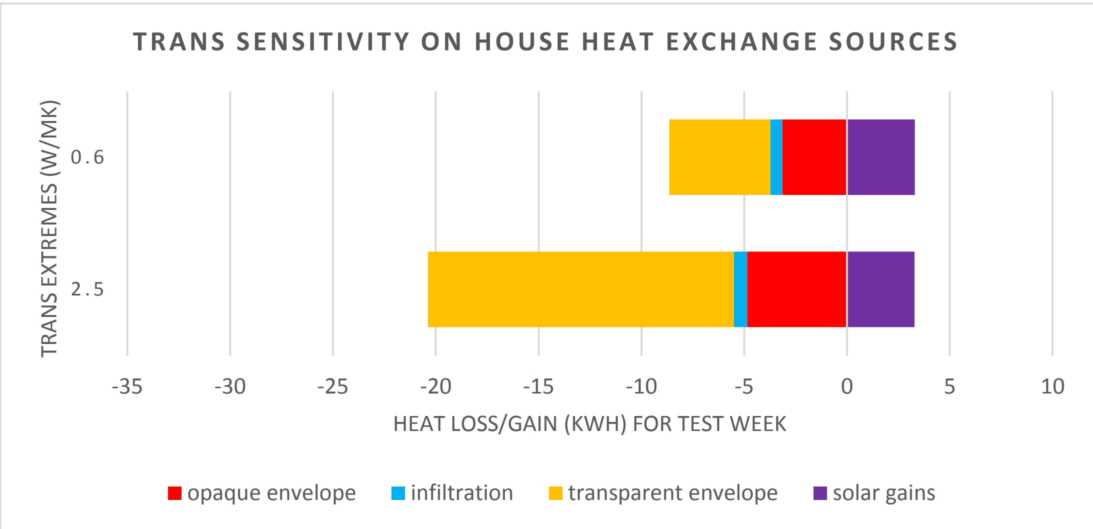


Fig. 34: Heat loss/gain with [trans] fluctuation

Similarly to the opaque envelope conductivity, the effect on error is not significant for the range of allowed values between 0.6-2.5 W/m^{2}K (and thus for a typical energy efficient double glazing). From the shape of the diagram, an estimated value can be around 1-2 W/m^{2}K. On the other hand, the effect on energy is significant, again possibly because of the large surface area in comparison with the volume. Thus the heat losses are seemingly high but the temperature is not changing in the same rate. Again the coupling effect with the conductivities can be observed.

Transparent envelope solar gain [solar]

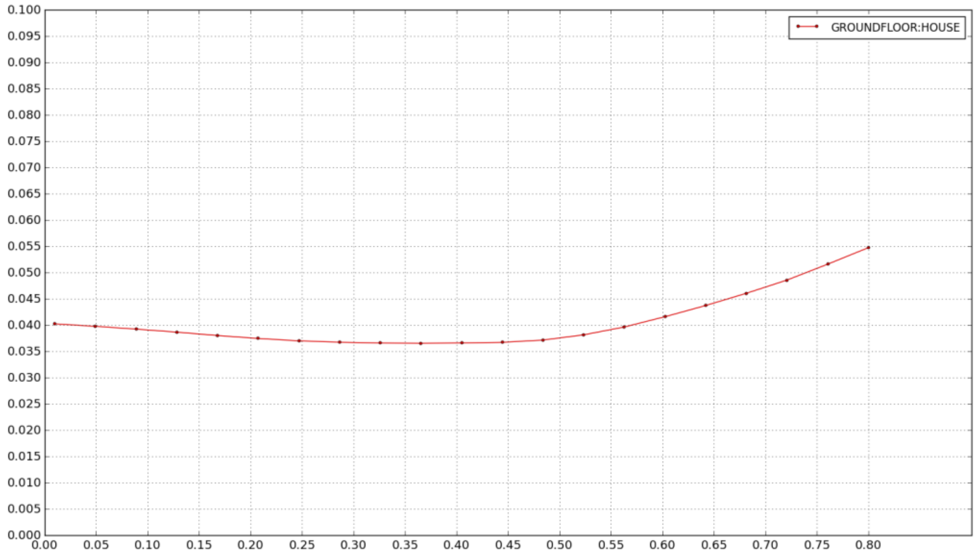


Fig. 35 Error diagram for fluctuating solar gain

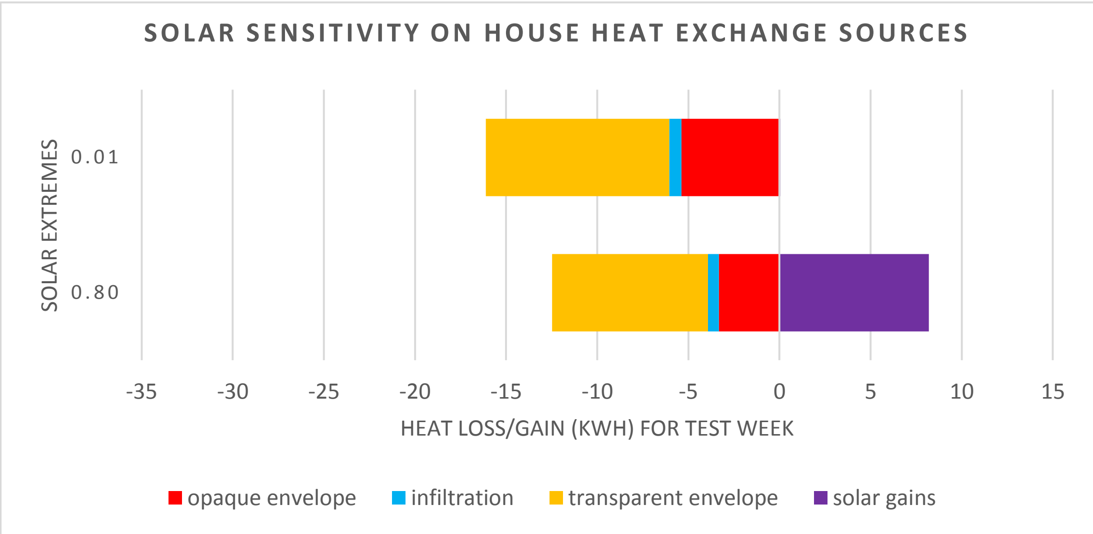


Fig. 36: Heat loss/gain with [solar] fluctuation

The solar heat gains are also not showing a significant effect on the error, with a 2% in their whole range of values. Nevertheless, its rate of effect changes rapidly as its value moves to the second half of its range, both for energy and error. The estimated plateau of values are around 0.3-0.5, close to the 0.4 that is given by the manufacturer. A coupling effect is seen on the thermal properties of the envelope, as the rise of temperature due to solar gains yield more heat losses.

Total sensitivity analysis

The infiltration is the most important parameter with the opaque envelope conductivity and solar gains following. They almost always have an effect on the energy and for the infiltration also on error. The transparent envelope U-value has a smaller effect, while the flow exponent has no effect at all. The max and min energy values are summed and shown in the following charts, with the total heat losses sum in the bottom (kWh).

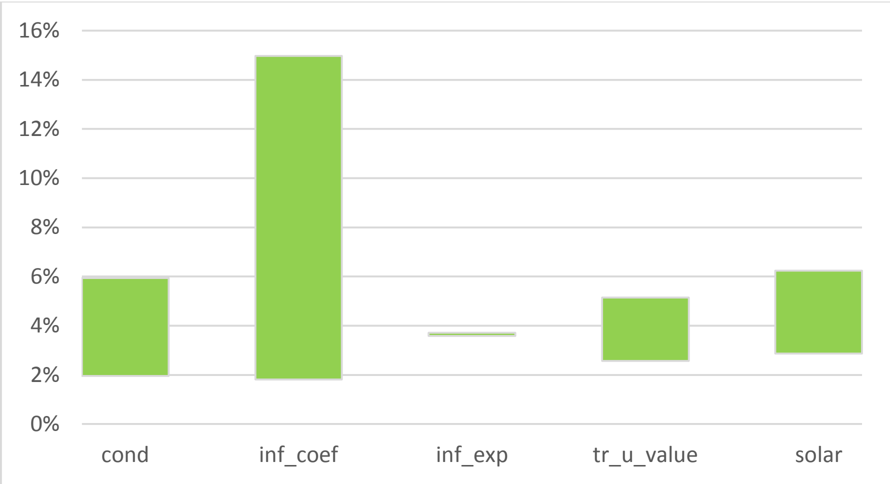


Fig. 37 CV(RMSE) error range per parameter range

5.2 Design verification results – New house

The target of this experiment is to examine the validity of the design assumptions in the as-built situation and use them as an indication of the size of the calibrated parameters. As mentioned in the research proposal in Chapter 2, a multi-zone model is proposed for verifying a new house. A reason for this is that it can possibly provide a more detailed insight about the conditions of each zone-room through the multiple verification points. The creation of such model is possible for a new house, as the design parameters of each separate building component are relatively easy to find from the design documentation and as-built construction plans.

Nevertheless, in order to test the assumption of the multi-zone model (each room is a zone) versus the opposite assumption (the house forms one zone) the verification is also performed with a single zone model. As mentioned in the chapters before, the main assumption behind a single zone model is the significant air exchange between the rooms and the limited insulation in the interior walls. The model is created with average component properties, using the surfaces areas as weights and with one verification point, the sensor in the living room.

The results are presented first in the forms of plots, showing the simulation (in red) and measured curves (in blue) for a representative period. Then the aggregated results are shown and a small statistical analysis is performed.

Results with a multi-zone model

<u>Temperature plots</u>

In the following plots the results of a period in January (of total duration equal to 2.7 days), is presented. From a visual observation it can be seen that there is some convergence, varying for each zone while the simulation curves follow more or less the drop rate of the measured data. The CV(RMSE) error is varying from 9.52% for the bathroom to a 1.81% for the living room. The RMSE is around 1.5°C for the bathroom and less than 0.3°C for the living room. Also, it can be noted that there is some difference in the measured temperatures between the different zones, e.g. the bathroom starts on a 17.4°C temperature while living room on a 20°C.

Nevertheless, for all the plots here and on average for all periods, the simulation curve is below the measured counterpart (i.e. the MBE is below zero). That may mean that the design values of the parameters are conservative and that the house is even better protected from heat losses than it was designed. Other possible explanations will be presented in the discussion in Chapter 7.

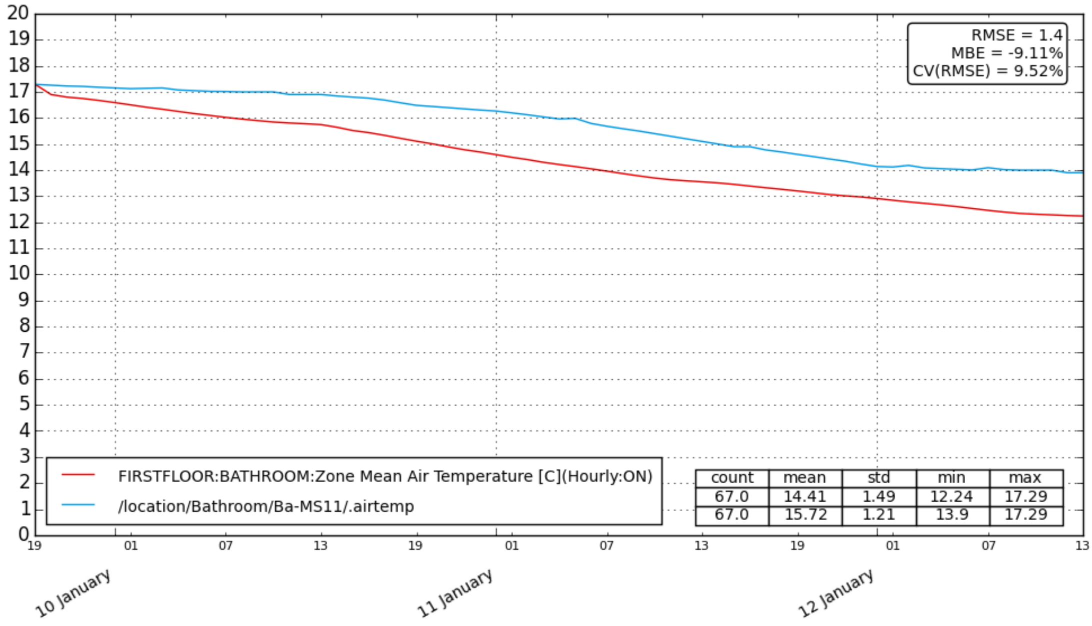


Fig. 38 Bathroom zone convergence – 10-12 January (Blue – Measured, Red – Simulation)

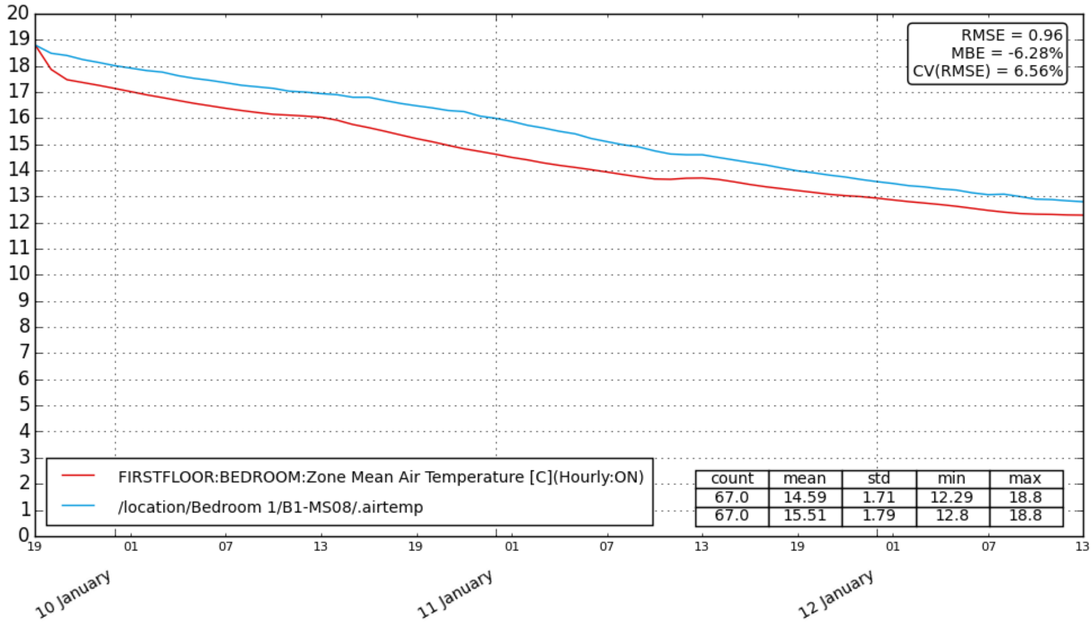


Fig. 39 Bedroom zone convergence – 10-12 January (Blue – Measured, Red – Simulation)

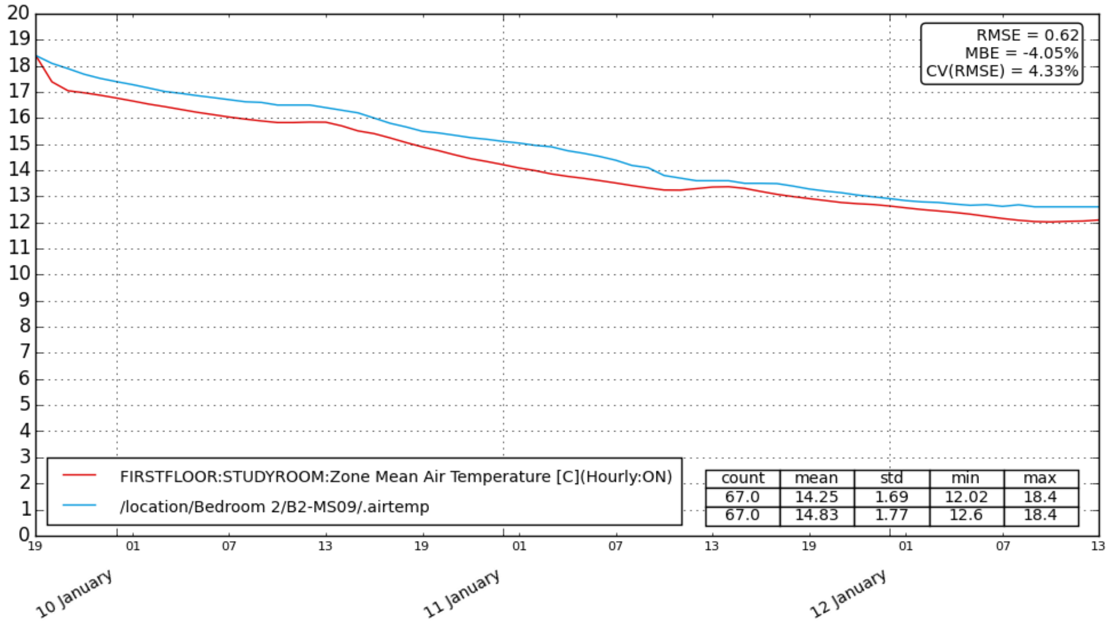


Fig. 40 Studyroom zone convergence – 10-12 January (Blue – Measured, Red – Simulation)

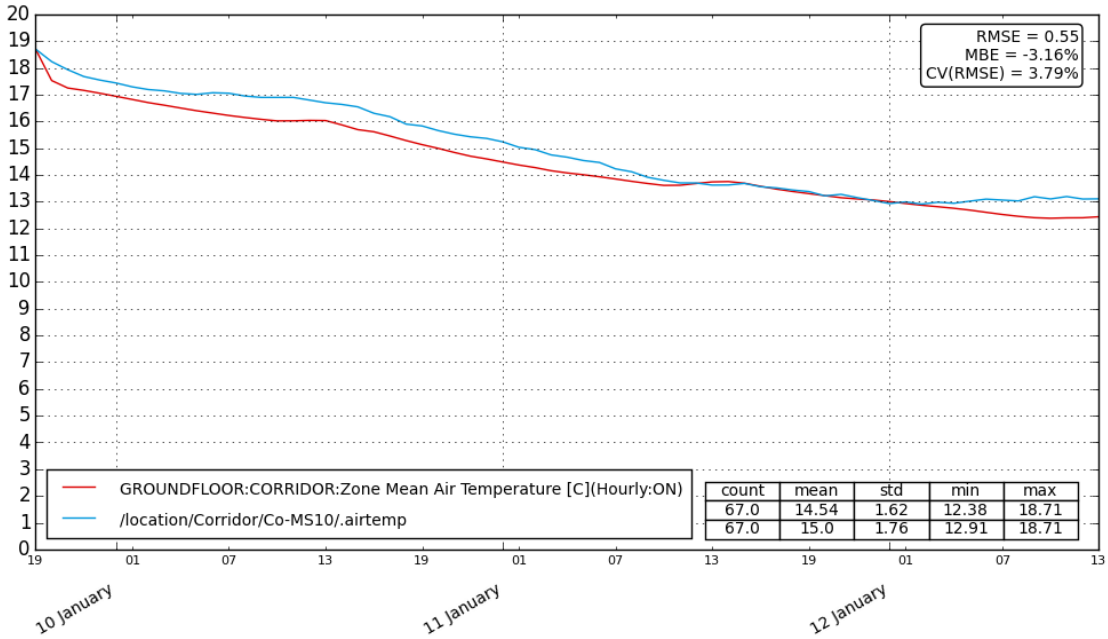


Fig. 41 Corridor zone convergence – 10-12 January (Blue – Measured, Red – Simulation)

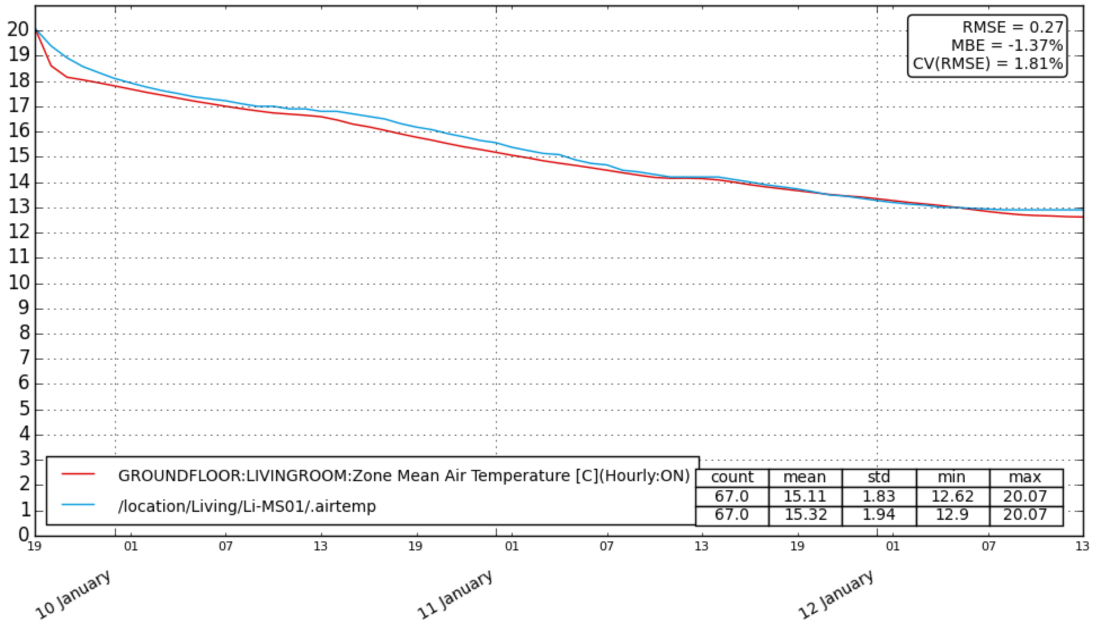


Fig. 42 Living room zone convergence – 10-12 January (Blue – Measured, Red – Simulation)

Error statistical analysis

Similar patterns can be observed in the rest of the zones and comparison periods as presented in the following statistical tables. For offering a concentrated view of the total convergence of the house, the mean value of the errors from all the zones is calculated, weighted on their volume size. Since the living room is by far the larger zone, it can be noticed that the weighted mean values are close to the values for this zone. As mentioned in the visual inspection of the plots before, the MBE is below zero on average for all zones and the weighted mean. Periods with an MBE above zero do exist as shown by the positive max values. But they are far from the average values, as suggested by the small standard deviations, with the possible exception of the living room. The largest CV(RMSE) error on average can be found for the corridor (7.2%) and the bathroom (6.4%) while the smallest is in the living room (4.3%).

GROUNDFLOOR:LIVINGROOM

	MBE (%)	RMSE (°C)	CV(RMSE) (%)
MAX	11.2%	1.6	11.6%
MIN	-8.2%	0.2	0.8%
AVERAGE	-2.0%	0.7	**4.3%**
STDEV	4.4%	0.4	2.9%

GROUNDFLOOR:CORRIDOR

	MBE (%)	RMSE (°C)	CV(RMSE) (%)
MAX	6.8%	2.0	14.3%
MIN	-13.7%	0.4	1.9%
AVERAGE	-5.4%	1.2	**7.2%**
STDEV	5.3%	0.5	3.6%

FIRSTFLOOR:BATHROOM

	MBE (%)	RMSE (°C)	CV(RMSE) (%)
MAX	2.7%	2.2	15.3%
MIN	-14.8%	0.2	1.2%
AVERAGE	-5.6%	1.0	**6.4%**
STDEV	4.7%	0.6	4.3%

FIRSTFLOOR:BEDROOM

	MBE (%)	RMSE (°C)	CV(RMSE) (%)
MAX	3.8%	1.7	12.2%
MIN	-11.7%	0.3	1.9%
AVERAGE	-4.8%	0.9	**5.6%**
STDEV	3.4%	0.4	2.6%

FIRSTFLOOR:STUDYROOM

	MBE (%)	RMSE (°C)	CV(RMSE) (%)
MAX	5.2%	1.8	12.4%
MIN	-11.8%	0.2	1.3%
AVERAGE	-3.6%	0.8	**4.8%**
STDEV	3.8%	0.4	3.0%

Weighted mean

	MBE (%)	RMSE (°C)	CV(RMSE) (%)
MAX	7.7%	1.5	10.5%
MIN	-10.0%	0.3	1.8%
AVERAGE	-3.2%	0.8	**4.9%**
STDEV	4.0%	0.3	2.5%

Table 8: Statistical analysis for the errors of all different zones

Error comparison between the periods

The weighted mean errors collected for the studied measured periods can be found below. In the CV(RMSE) diagram, it can be seen that for most the error is below 10%. The larger error values can be found mostly in the winter months of January-March. This is rather expected as the larger temperature difference between exterior and interior leads to higher heat losses due to the apparent inaccuracy of the design values.

In the MBE diagram, it can be confirmed what was mentioned earlier, that in most periods the design parameters seems to be conservative.

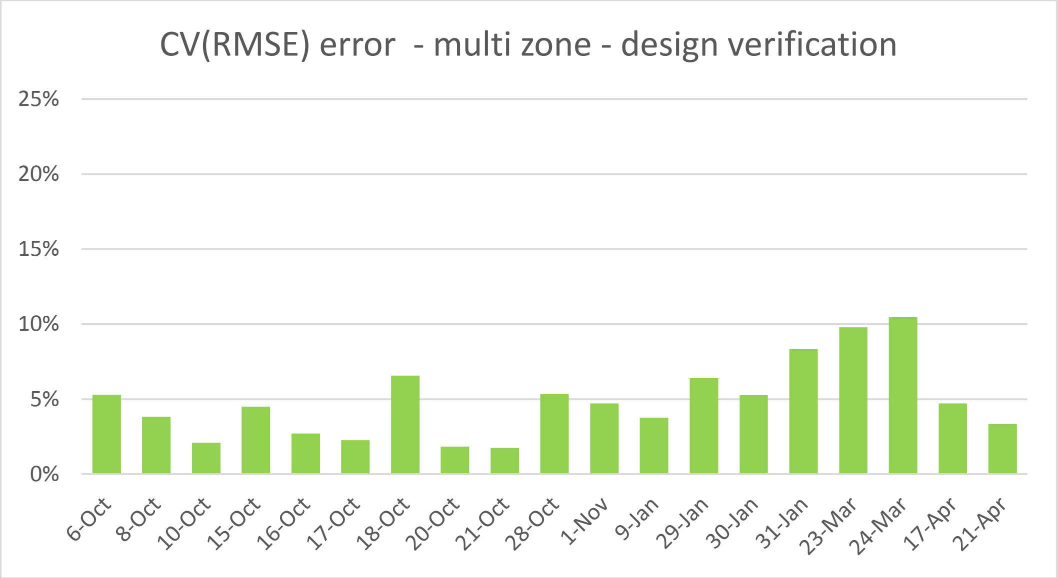


Fig. 43: CV(RMSE) average weighted error for the available periods

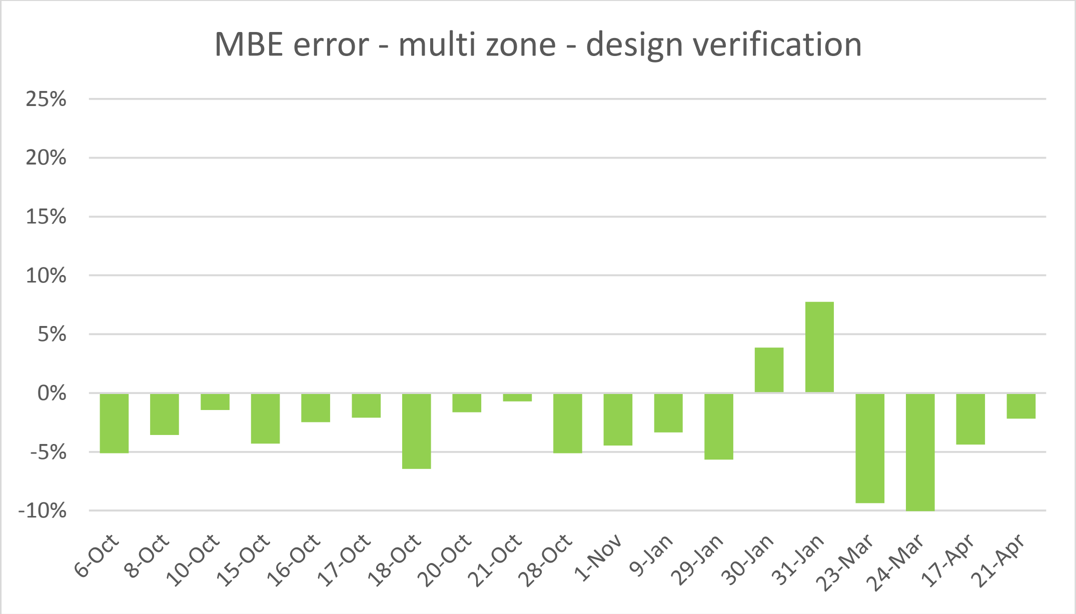


Fig. 44: MBE average weighted error (negative shows overconservative design parameters)

Results with a single-zone model

Temperature plots

In the following the temperature plot of the same period in January is presented to compare with the ones from the multi-zone model before. Furthermore, the plot of the period with the largest CV(RMSE) error is shown. The more striking difference with the plots below is that the simulation curves are now above their measured counterparts. That suggests that there more occurring heat losses in reality than the ones from this specific simulation (using average component values). This difference becomes more apparent on the February, where more than 20% error can be found above the measured data, suggesting large heat losses. This can be explained from the interior-exterior temperature difference, where for the period in January is between 6-10°C and for the period on February is between 0-6°C.

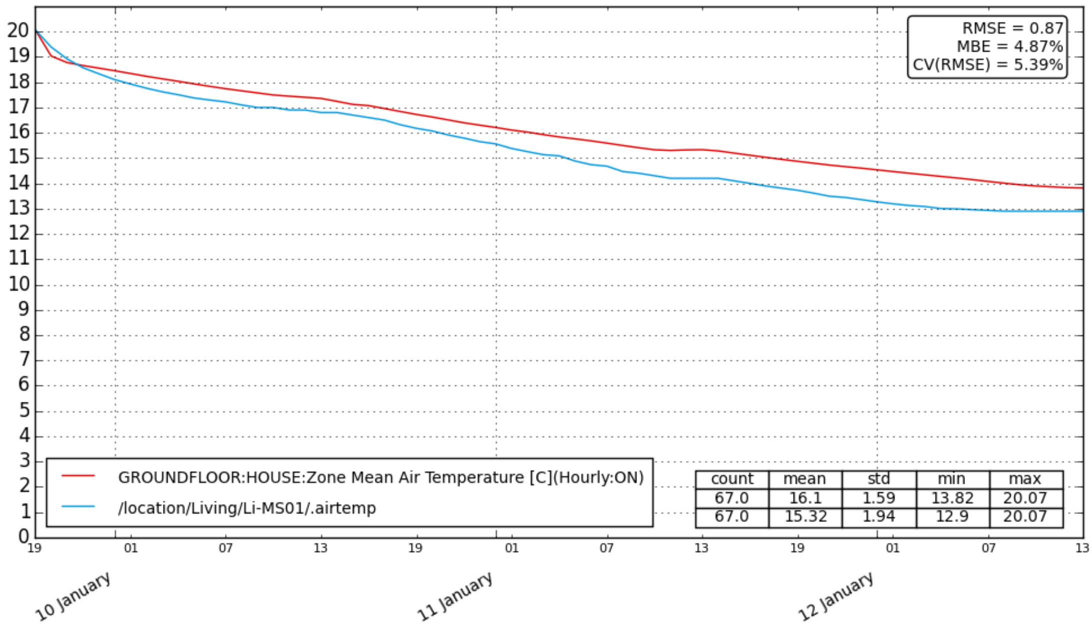


Fig. 45 Single zone convergence – 10-12 January (Blue – Measured, Red – Simulation)

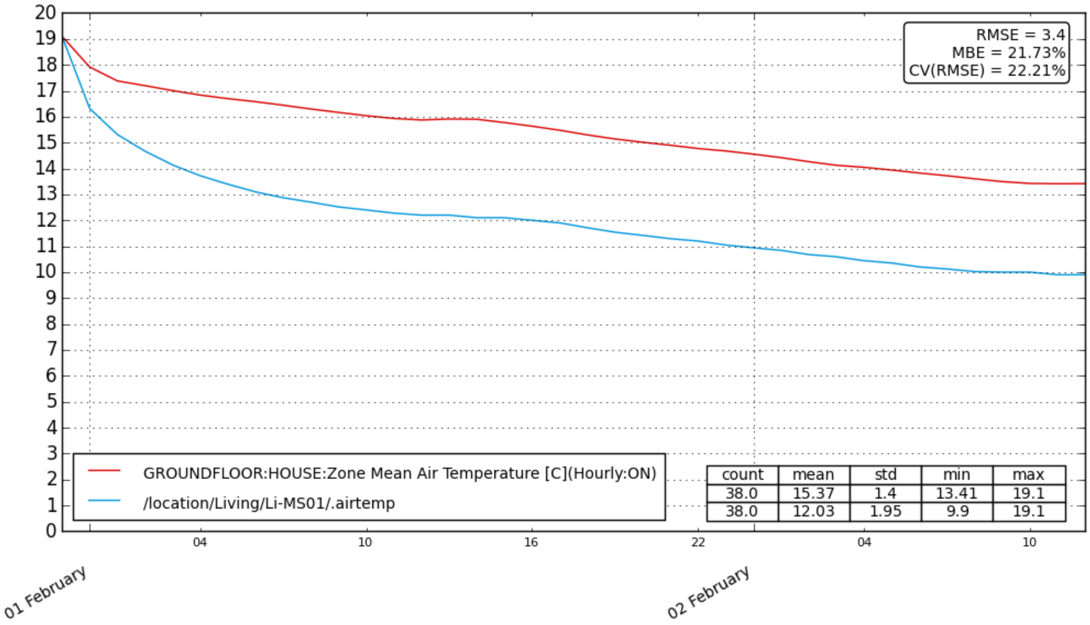


Fig. 46 Single zone convergence – 1-2 February – largest MBE (Blue – Measured, Red – Simulation)

<u>Error statistical analysis</u>

Again opposite from the multi-zone model below, the statistical analysis shows a positive MBE on average, although there is also a significant number of periods with negative MBE. Also, it can be noted that the max RMSE and the CV(RMSE) errors are far larger than before, with the latter reaching a 22.2% error for the February period, as presented before in the plots. Nevertheless, the average error is 4%, which is not far from what was found before for the weighted mean of the multi-zone model (4.9%).

SINGLE ZONE

	MBE (%)	RMSE (°C)	CV(RMSE) (%)
MAX	21.7%	3.4	22.2%
MIN	-9.2%	0.1	0.3%
AVERAGE	0.9%	0.7	**4.0%**
STDEV	6.1%	0.8	5.1%

Table 9: Statistical analysis for the error of the single zone

Error comparison between the periods

The error diagram for the CV(RMSE) shows a similar image as before, with larger errors for the periods in January. Again, the largest errors can be found for the winter periods, due to the same reason as in the multi-zone model. In contrary, the MBE diagram show a mix of positive and negative errors in comparison with the almost uniformly negative errors in the multi-zone model.

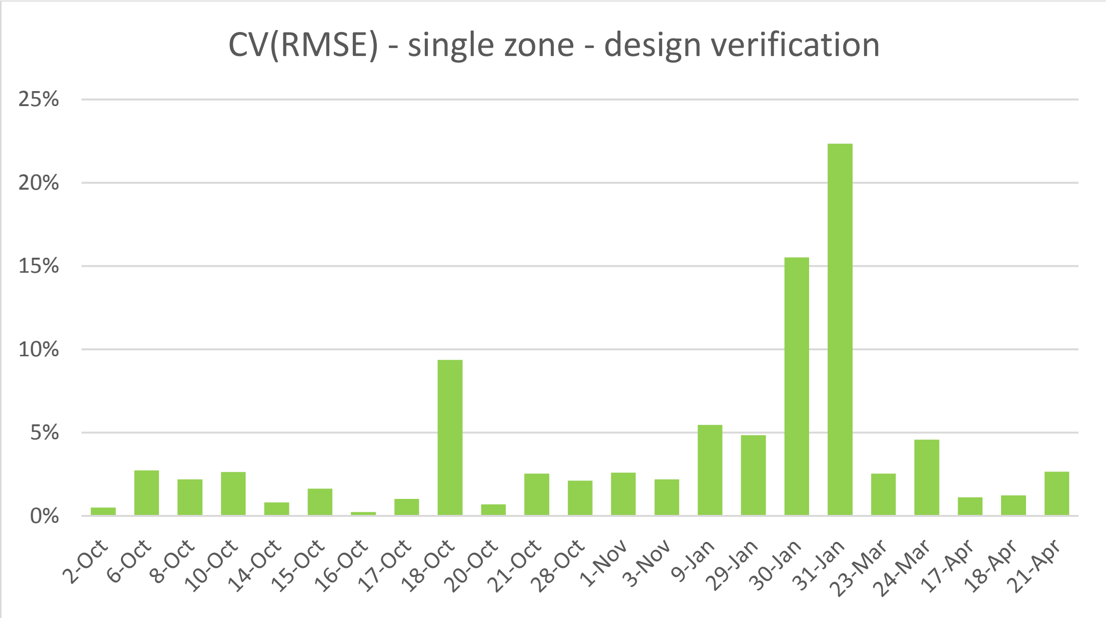


Fig. 47 CV(RMSE) error for the available periods

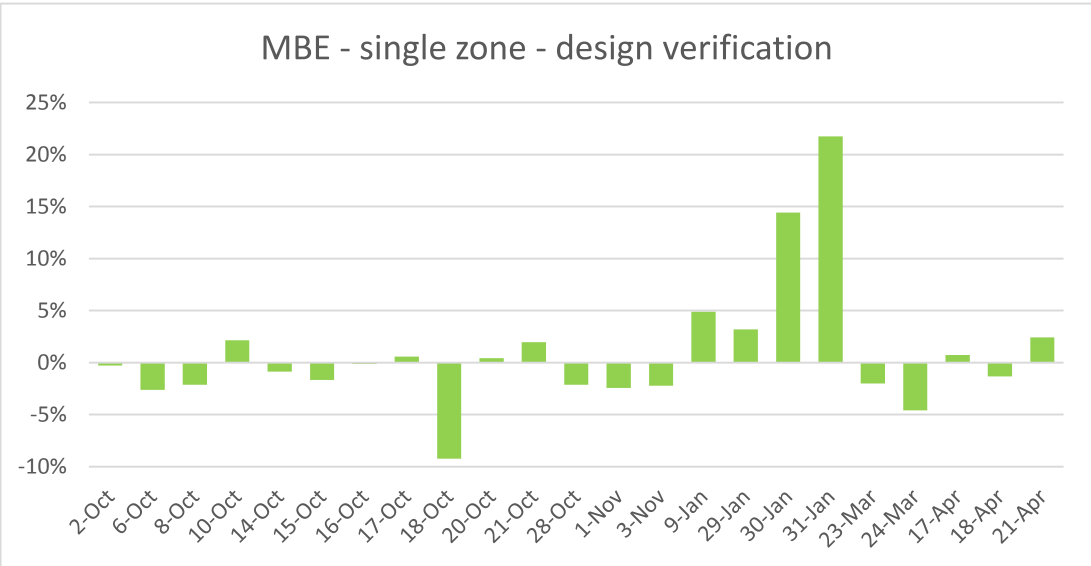


Fig. 48 MBE error for the available periods (negative shows overconservative design parameters)

5.3 Calibration Results – Old house

In the following the results of the calibration of Pal House to the measured data from the database is shown. The measured data is the same used for the verification of the design values with the single-zone model. This model is only used in the calibration for the reasons given in the problem statement in Chapter 2. Nevertheless, within these model, two possible sets of parameters will be examined. The first set includes only the opaque envelope equivalent conductivity (*cond*) and the infiltration coefficient (*inf_coef*). In the second, the transparent envelope U-value (*trans*) and the solar gains coefficient (*solar*) is added to the parameters of the first set.

This separation is performed in order to study the two most unpredictable parameters separately. The other two are relatively easier to establish, even to an older home as it they have more standardised values. The main target of the calibration process here is to find a range of values to indicate where the possible real parameter sets lies. In the results of the calibration shown below, the convergence diagrams and the temperature error diagrams are presented first, to indicate the quality of the calibration. Then, the different parameter and error ranges are presented in diagrams per period as well as in statistical analysis.

2-parameter calibration

<u>Convergence and data fitting</u>

As can be observed in the following diagrams for selected periods, the calibration algorithm convergence ability is significant, leading to satisfying data fitting.

Fig. 49: Algorithm convergence for 15-Oct

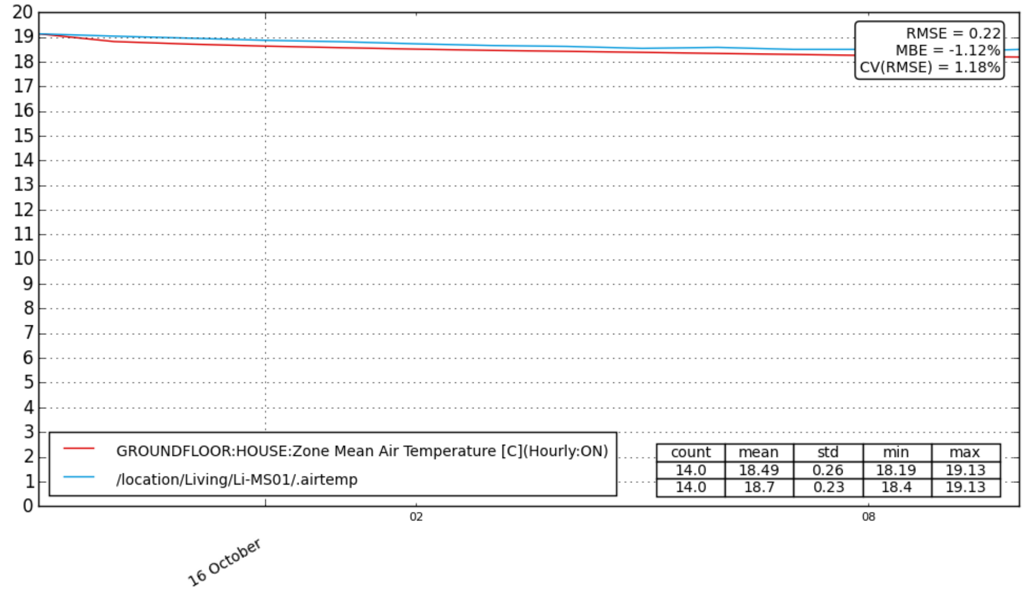


Fig. 50: Simulation data fitting for 15-Oct

<u>Parameter and error range</u>

The results of the calibration can be observed in the following figures. For the conductivity it can be seen that the average value is around 0.035 W/mK with a small standard deviation of 0.013 as suggested also by the diagram while few outlier can be seen. In contrary for infiltration, there are some substantial outliers with an order of magnitude difference from the mean value. Also, the total error is on average around 1.5% with a 1.1% standard deviation, suggesting the large variety between periods, as seen in the error diagram.

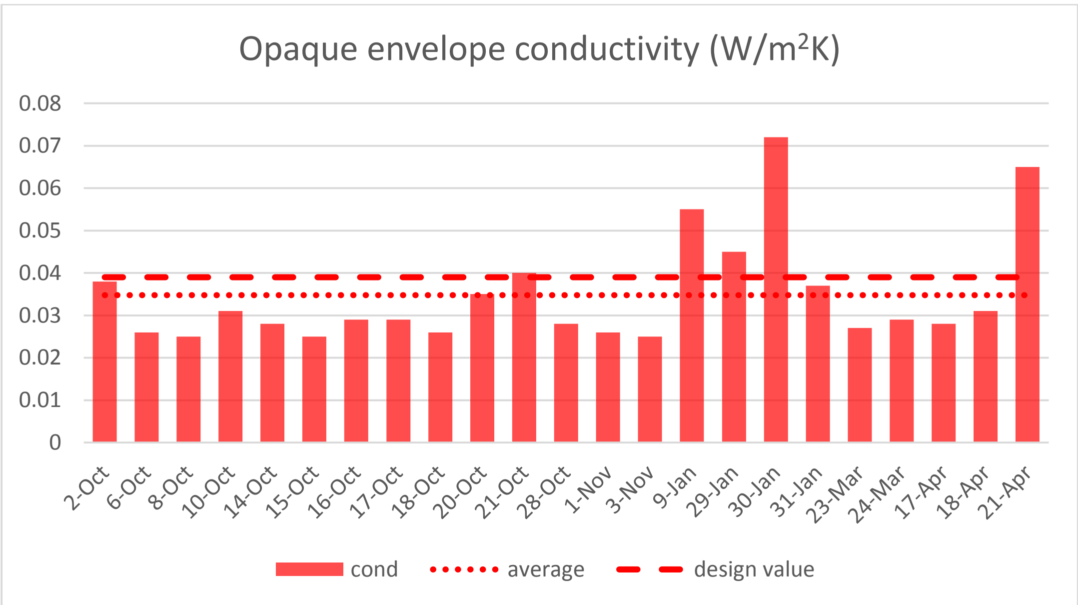


Fig. 51: Calibration resulting [cond] value per period (2-parameter run)

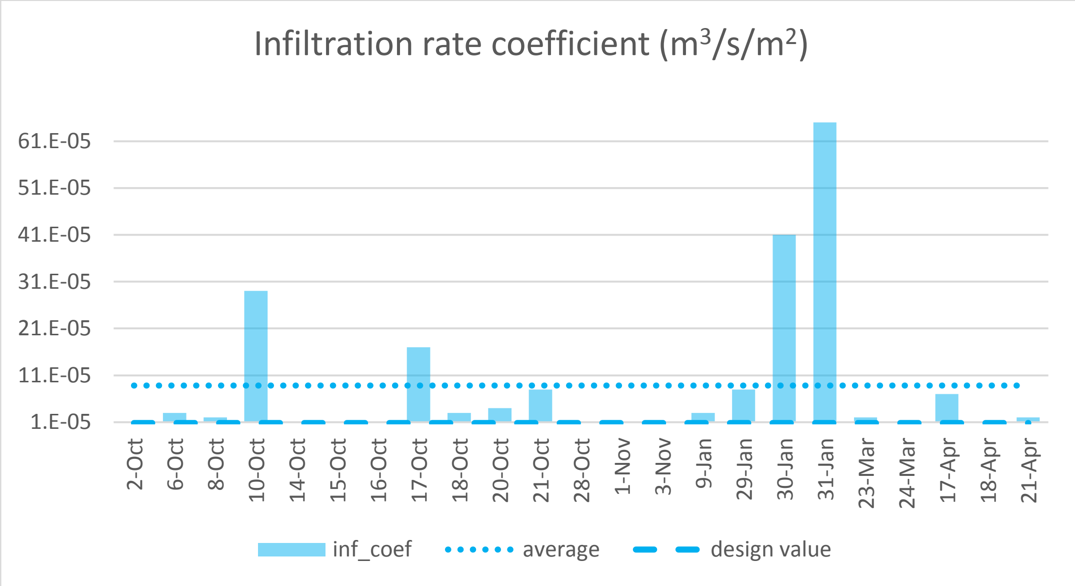


Fig. 52: Calibration resulting [inf_coef] value per period (2-parameter run)

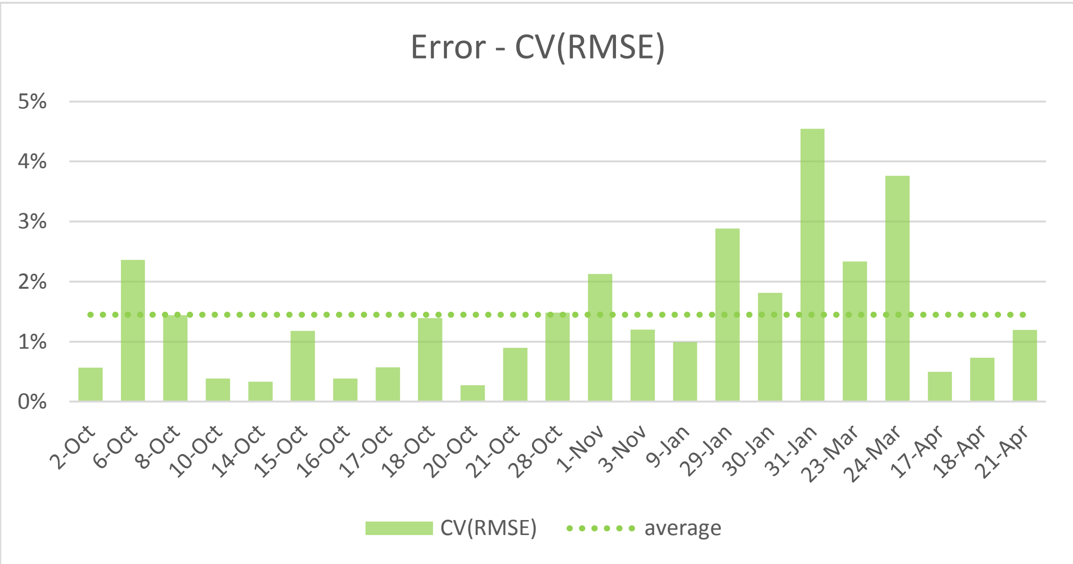


Fig. 53: Error per period - CV(RMSE) (2-parameter run)

2-parameter calibration

	cond (W/m²K)	**inf_coef** (m³/s/m²)	**error** (%)
MAX	0.072	65 E-05	4.5%
MIN	0.025	1 E-05	0.3%
AVG	**0.035**	**9 E-05**	**1.5%**
SDEV	0.013	15 E-05	1.1%

Table 10: Statistical analysis – 2-parameter calibration results

4-parameter calibration

Convergence and data fitting

Similarly with the results before, there seems to be no large difference due to the calibration of 4 parameters instead of 2.

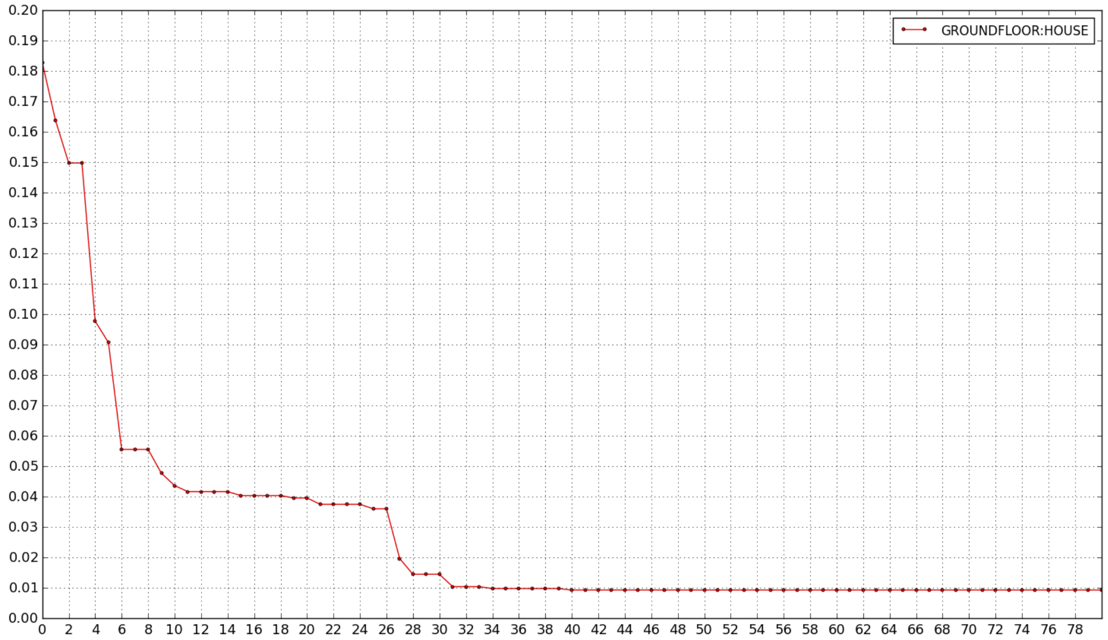


Fig. 54: Algorithm convergence for 9-Jan

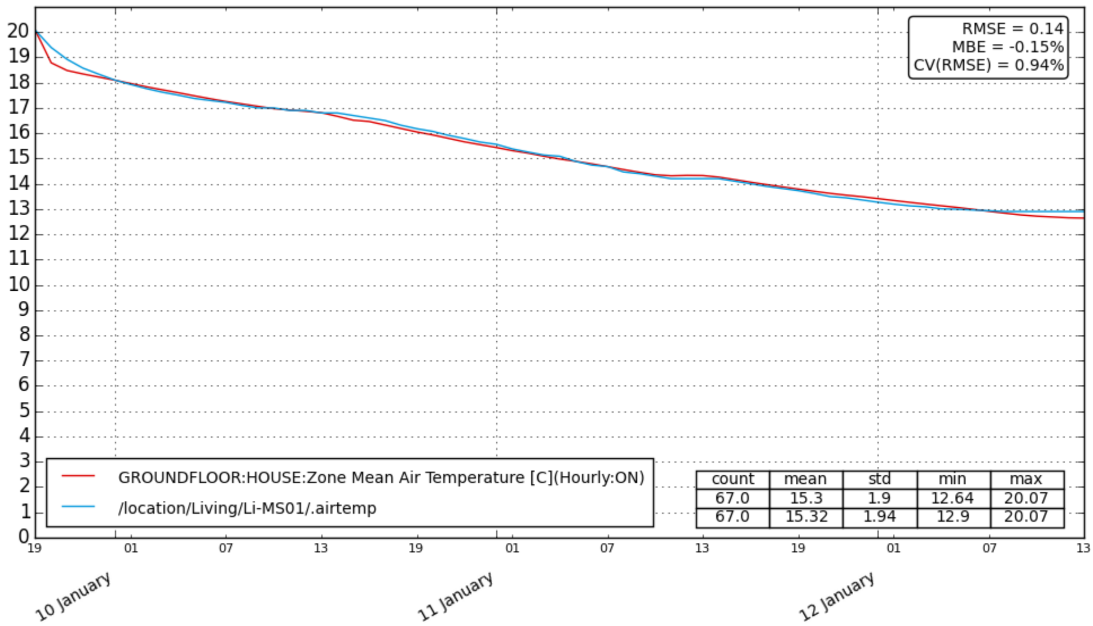


Fig. 55: Simulation data fitting for 9-Jan

Parameter and error range

Compared with the 2-parameter calibration, the results on the two first parameters are not very different. The average conductivity is higher, while the outliers are stronger, i.e. there is a value of 0.14 and one of 0.12 W/mK while most of the others are around 0.04 W/mK. Nevertheless, this very high value is not due to a problematic calibration as their corresponding error is not high e.g. about 0.5% error for the 0.14 W/mK conductivity. Infiltration rate is showing similar behavior with before and with an average value of 0.0007 which is very close to the 0.0009 found before. The transparent envelope U-value shows also some variety, while it has to be noted that the average value is close to 1.3 W/m2K, which is the design value for a HR++ double glazing. On the contrary, the average value of 0.624 for the solar gains is higher than the 0.4 value from the design. Finally, it is noted that the total error is smaller on average and with less standard deviation than in the 2-parameter calibration.

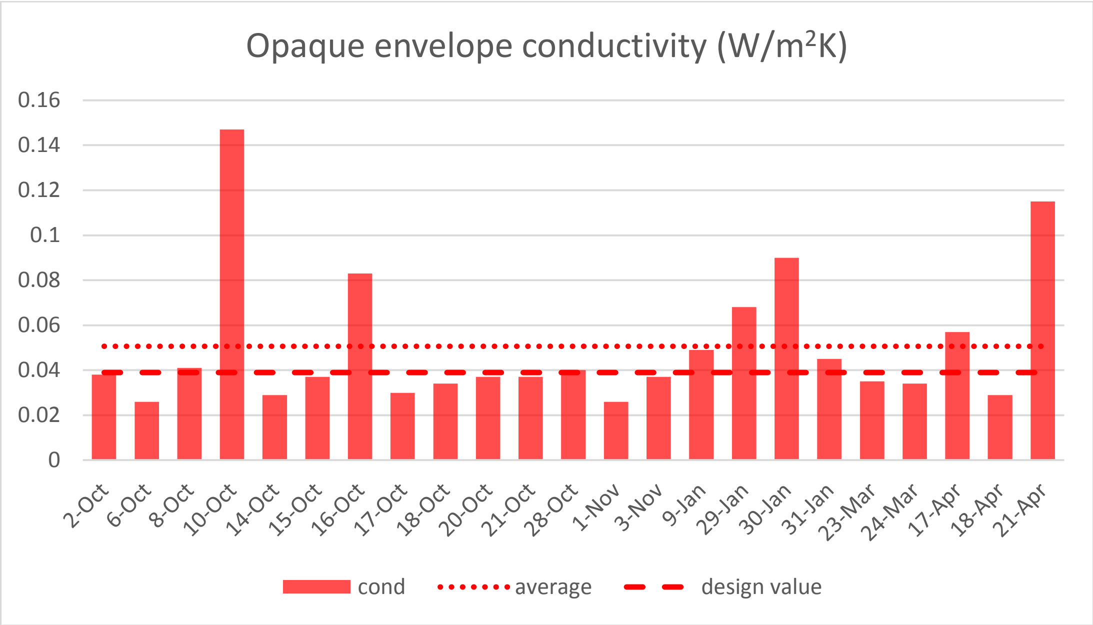


Fig. 56: Calibration resulting [cond] value per period (4-parameter run)

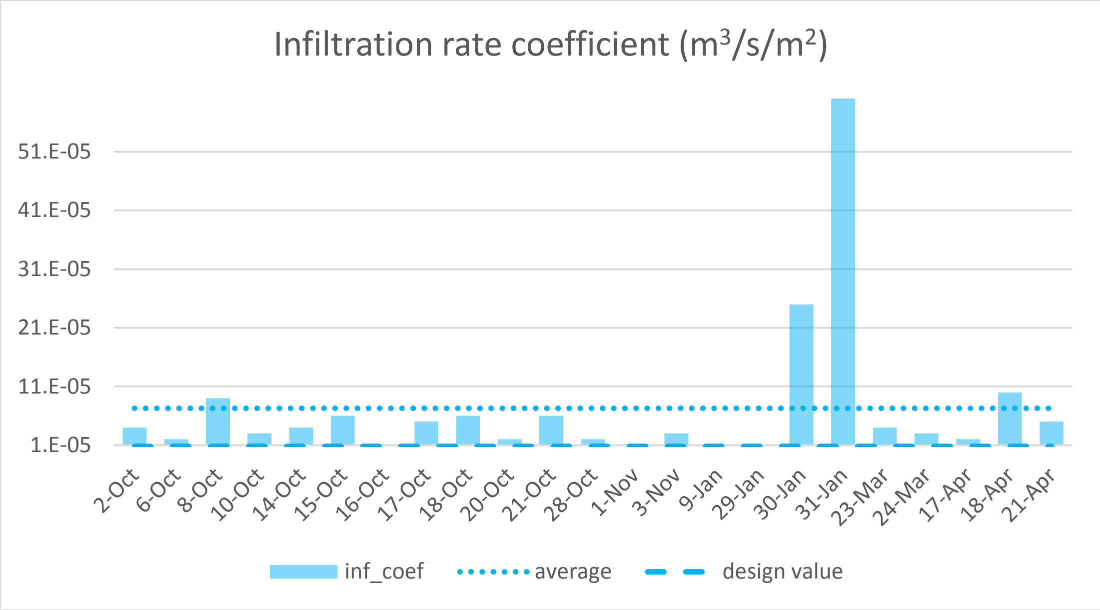


Fig. 57: Calibration resulting [inf_coef] value per period (4-parameter run)

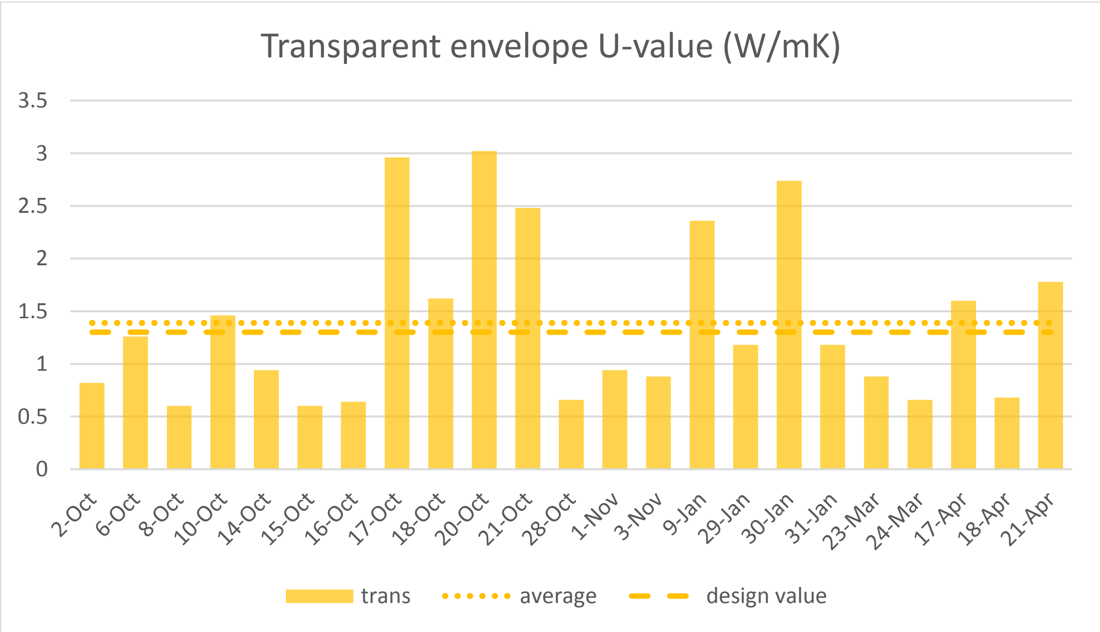


Fig. 58: Calibration resulting [trans] value per period (4-parameter run)

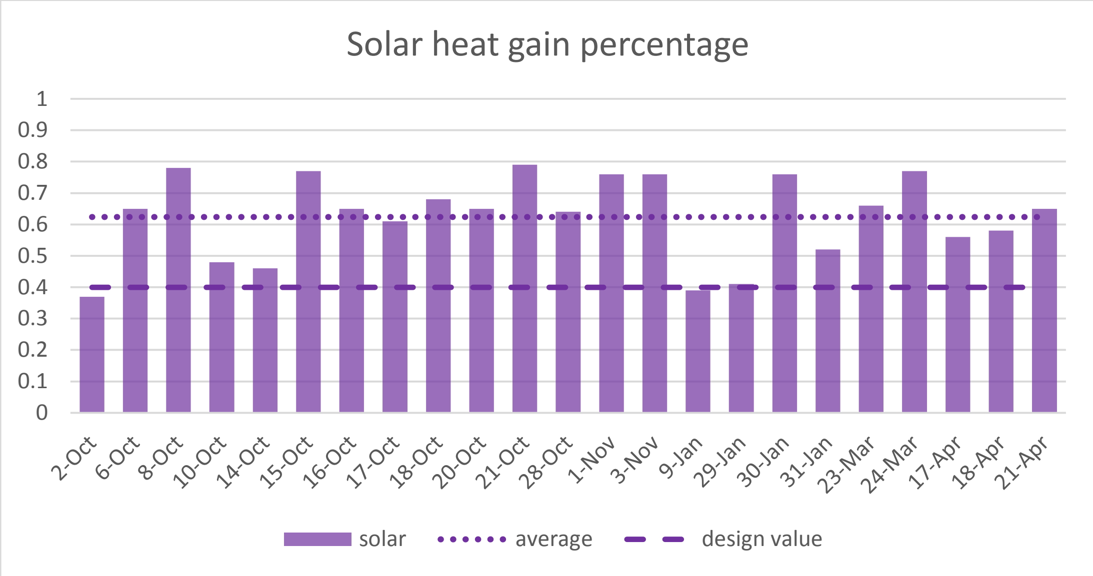


Fig. 59: Calibration resulting [solar] value per period (4-parameter run)

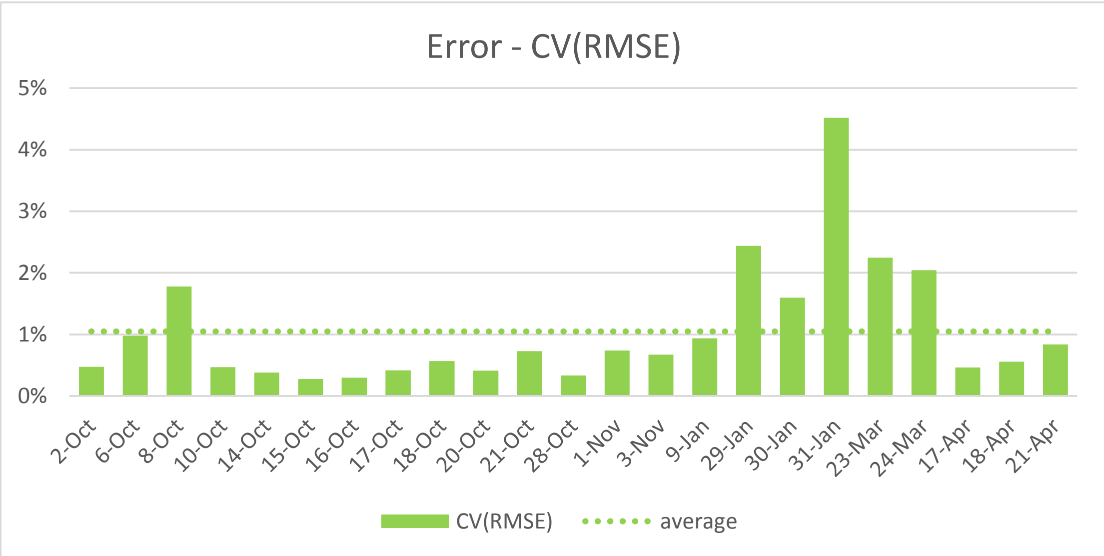


Fig. 60: Error per period - CV(RMSE) (4-parameter run)

4-parameter calibration

	cond (W/m^2K)	**inf_coef** ($m^3/s/m^2$)	**solar**	**trans** (W/mK)	**error** (%)
MAX	0.147	62 E-05	0.79	3.02	4.5%
MIN	0.026	1 E-05	0.37	0.60	0.3%
AVG	**0.051**	**7 E-05**	**0.62**	**1.39**	**1.1%**
SDEV	0.030	13 E-05	0.13	0.78	1.0%

Table 11: Statistical analysis - 4 parameter calibration results

6. Validation

In the following chapter two kinds of validation are performed. The first one is about the process with the genetic algorithm used for the calibration, in order to show how effective can possible be by itself, without adding up the uncertainties of measured live data. The second is about validating the calibration results from the previous Chapter 6, by using some of them as training data for creating a model and then calculating the deriving error on the rest.

6.1 Validation of calibration process with known parameters

The validation of the process can be performed with various methods. The most straightforward would be to create some simulated data with a specific known set of parameters and then try to find these with the calibration. Of course, a variety of configurations can be tested in relation with this validation such as the duration of measured data taken or the convergence limit. To avoid an extended, complicated analysis that might go out of scope, the two scenarios from 4.2 are chosen for validation, with a convergence limit of 0.5% error. The results are presented as sets of parameters deriving from calibration compared with the target parameters (underlined). The closest values to the target parameters are noted on bold.

Furthermore, a comparison with a multi-parameter calibration is presented in order to justify that the use of such an approach is not appropriate for calibrating with a BPS simulation. Finally a statistical analysis of the time needed for a variety of calibration runs is also given. The last two sections can be found in the appendix section 9.6.

Single long period scenario – process validation with known parameters

In the following, the scenario of using a single long period (e.g. one week) for calibration is tested against known parameters. The week is taken as 24-30 November 2014. At first this is achieved by running 10 calibration runs with the same target and comparing the result average with the target set of parameters. Typical values for a well-insulated house are selected for targets. Then, 10 random sets of parameters are produced and the model is calibrated 3 times on each, again comparing the average results with the target parameters.

Opaque conductivity/Flow Coef/Solar gains ***(10 runs, same target)***

	cond (W/m²K)	inf_coef (m³/s/m²)	solar	error (%)
Target	0.080	80 E-05	0.70	
MAX	0.088	83 E-05	0.77	0.3%
MIN	0.073	76 E-05	0.53	0.1%
AVG	**0.079**	**80 E-05**	**0.66**	0.2%
SDEV	0.006	2 E-05	0.09	0.1%

Fig. 61: Results of 10 calibration runs with known parameters (one week of measured data)

Opaque conductivity/Flow Coef/Transparency ***(8x3 calibration runs, random targets)***

	cond (W/m²K)	inf_coef (m³/s/m²)	trans (W/mK)	error (%)	cond (W/m²K)	inf_coef (m³/s/m²)	trans (W/mK)	error (%)
Target	0.126	*46.0E-05*	0.83		0.114	*187.0E-05*	5.08	
Cal. runs	**0.134**	***47.0E-05***	**0.90**	***0.2%***	0.114	*190.0E-05*	4.60	*0.3%*
	0.116	*42.0E-05*	2.44	*0.4%*	0.107	*199.0E-05*	4.30	*0.5%*
	0.105	*34.0E-05*	4.72	*0.5%*	**0.116**	***186.0E-05***	**5.14**	***0.3%***
Target	0.233	*62.0E-05*	0.72		0.126	*136.0E-05*	0.96	
Cal. runs	0.246	*59.0E-05*	0.94	*0.3%*	0.110	*116.0E-05*	4.28	*0.5%*
	0.248	*52.0E-05*	3.88	*0.4%*	**0.121**	***128.0E-05***	**1.96**	***0.2%***
	0.227	***65.0E-05***	**1.20**	***0.2%***	0.118	*129.0E-05*	2.14	*0.2%*
Target	0.227	*71.0E-05*	2.56		0.231	*85.0E-05*	2.52	
Cal. runs	0.227	*63.0E-05*	3.52	*0.3%*	0.222	*75.0E-05*	4.48	*0.4%*
	0.224	***70.0E-05***	**3.02**	***0.3%***	**0.223**	***87.0E-05***	**2.62**	***0.4%***
	0.215	*62.0E-05*	4.74	*0.3%*	0.229	*73.0E-05*	4.12	*0.4%*

Target	0.320	*14.0E-05*	5.01			0.233	*145.0E-05*	4.06	
Cal. runs	**0.326**	***9.0E-05***	**5.68**	***0.2%***		0.237	*152.0E-05*	2.80	*0.3%*
	0.343	*17.0E-05*	2.88	*0.3%*		0.229	*152.0E-05*	3.08	*0.3%*
	0.307	*21.0E-05*	4.66	*0.3%*		**0.222**	***148.0E-05***	**4.38**	***0.3%***

Fig. 62: Results of random calibration runs with known parameters (one week of measured data)

On the above results it can be observed that the opaque conductivity and the infiltration flow coefficient can reach the target values with significant accuracy. That means possibly that their effect in the fitness can be captured efficiently by the algorithm. This is not the case for the transparent envelope U-value, where significant differences can be found between the solutions while the convergence to the target value is smaller. Solar gain coefficient is relatively more accurate, but not to the levels of conductivity or flow coefficient where the standard deviation of their values are really small.

Furthermore, it is also shown that even for solutions below 0.5%, a number of calibration results should be used in order to perform a statistical analysis and extract useful results. This is the case for the calibration analysis with the measured data of the Pal House. However the evaluation of the number of calibration runs for a reliable statistical analysis goes beyond the scope of this study.

Multiple short periods scenario – process validation with known parameters

Here the second scenario of using multiple short periods (e.g. 12-24 hours each, 7 days in total) for calibration is tested against known parameters. This specific validation can be possibly used as a proof of concept for the calibration of the PaL House, as this happens with a similar scenario of measured periods. In order to support this further, the same durations are used for this validation, using although a known set of parameters to create measured data, and then calibrate against it. The calibration is then run for one time for each duration, leading to the results below. Furthermore, the calibration is also cross-validated in the same way as with the live measurements calibration, by using 3 random folds. Finally it is noted that for brevity, the analytic results for the parameter values are shown only for the opaque conductivity and infiltration rate.

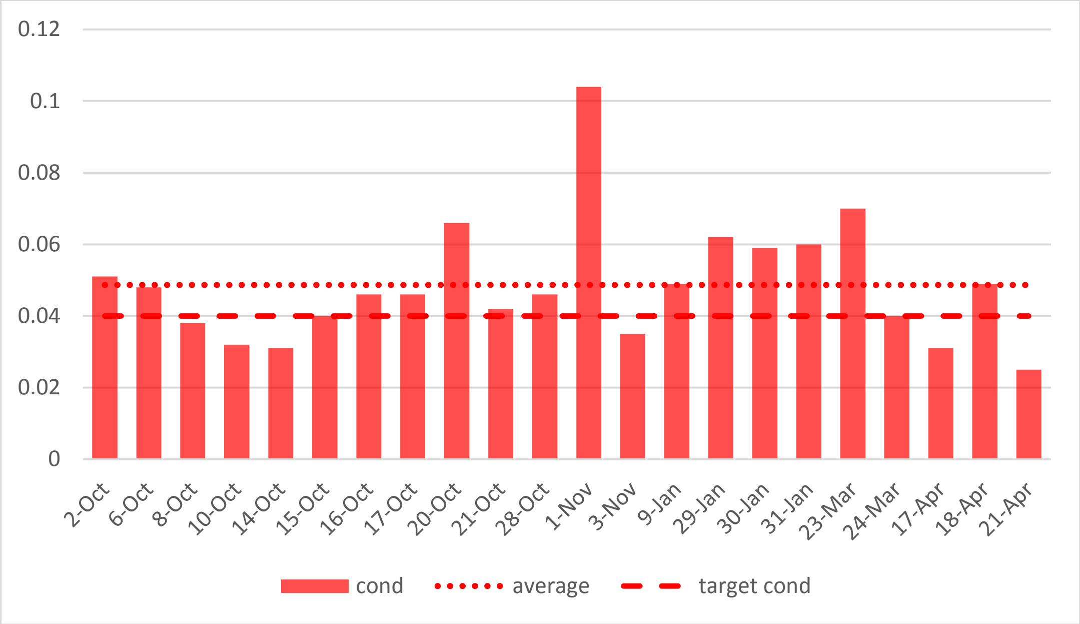


Fig. 63: Calibration resulting [cond] value per period (validation with known parameters)

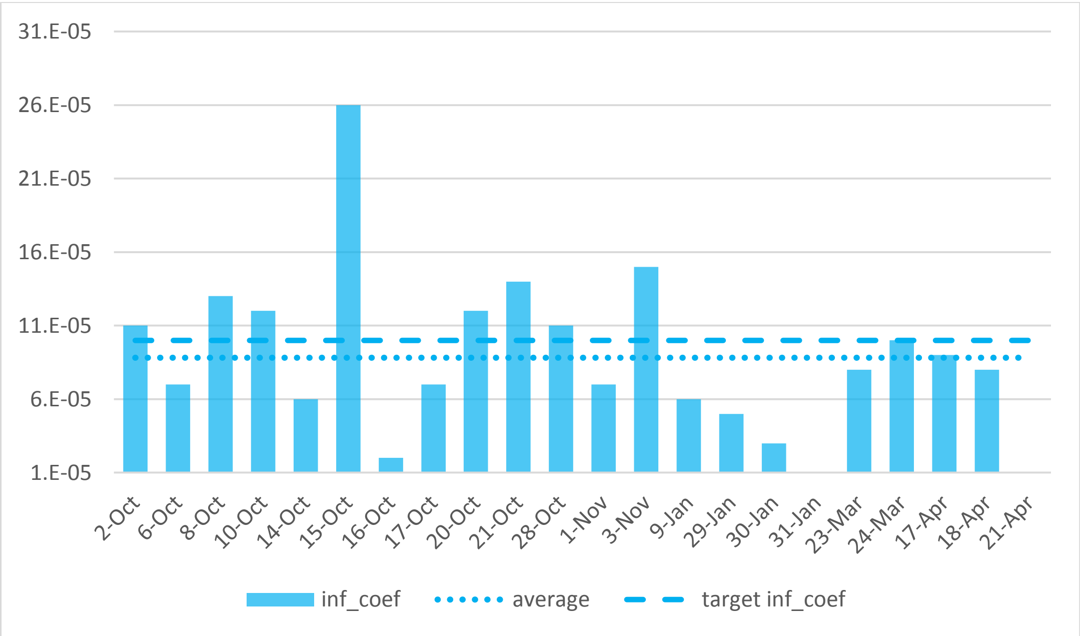


Fig. 64: Calibration resulting [ind_coef] value per period (validation with known parameters)

	cond (W/m^{2}K)	inf_coef (m^3/s/m^2)	solar	trans (W/mK)	error (%)
Target	0.040	10.0E-05	0.40	1.30	
MAX	0.104	26.0E-05	0.75	2.34	0.50%
MIN	0.025	1.0E-05	0.16	0.68	0.18%
AVG	**0.049**	**8.8E-05**	**0.48**	**1.35**	0.37%
SDEV	0.017	5.4E-05	0.20	0.53	0.10%

Table 12: Statistical analysis - multiple short period process validation

It can be observed that the target values of the parameters can be found with relative accuracy. The average values from all the runs results in a set of values close to the targets, for all parameters involved. The small deviation from the targets can be explained by the sensitivity of the parameters on the measurement size. As shown in the relevant analysis, for small measurement periods the resulting error can be minor for parameter values that are close to their targets. Thus, the algorithm cannot find the target solution with 100% accuracy but may find neighboring values with similar effect on the error. That is therefore the assumption for the calibration with live measured data.

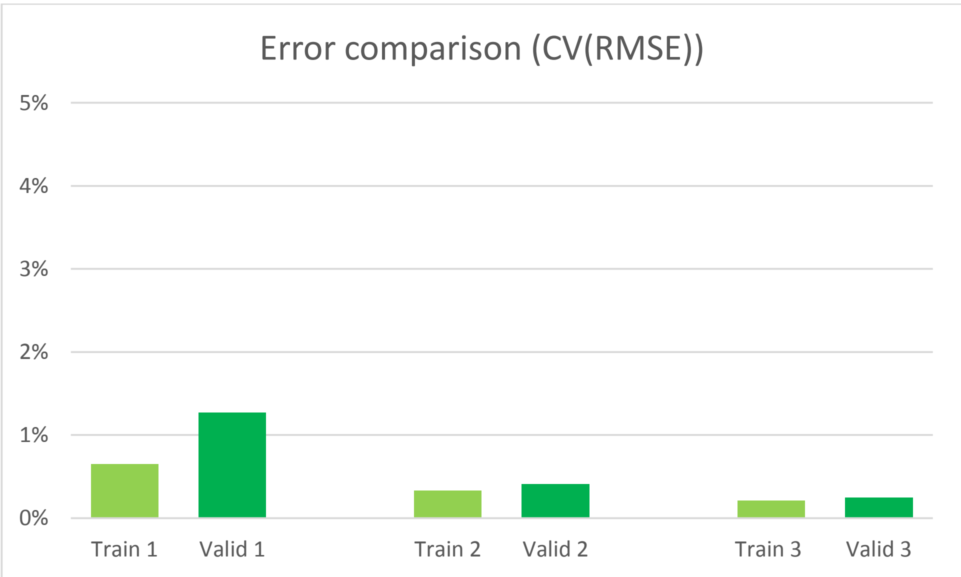


Fig. 65: Random fold validation of the calibration results with known parameters

The 3-fold validation of the results is showing a limited effect of overtraining the model. Especially for the last two, the effect is almost null while for the first it ranges on around 0.5% of overtraining error. It can be thus assumed that the quality of calibration was adequate for all the tested durations.

6.2 Validation of calibration with live measurements

As mentioned in Section 4.2, due to the limited max size of continuous Pal House measured data (i.e. less than three days), the only use case scenario that can be tested with real data is the one of many short measured periods. Therefore the validation effort on this chapter is focusing on this, by testing it in two ways. First, by using successive measurements over e.g. the course of two weeks and secondly by using sets of random measurements (folds) to train a model and then validate against the rest of the measurements.

Validation with successive measurements

In this validation the parameter sets from calibrating the first days of October are averaged and the resulting solution-model is used to calculate the error in the rest of the measured periods. The target is to achieve small difference between the training and the validation error, possibly implying that a solution derived by many successive short measurements can capture the real behavior of the house with accuracy. The periods selected and the results of the validation are shown in the following.

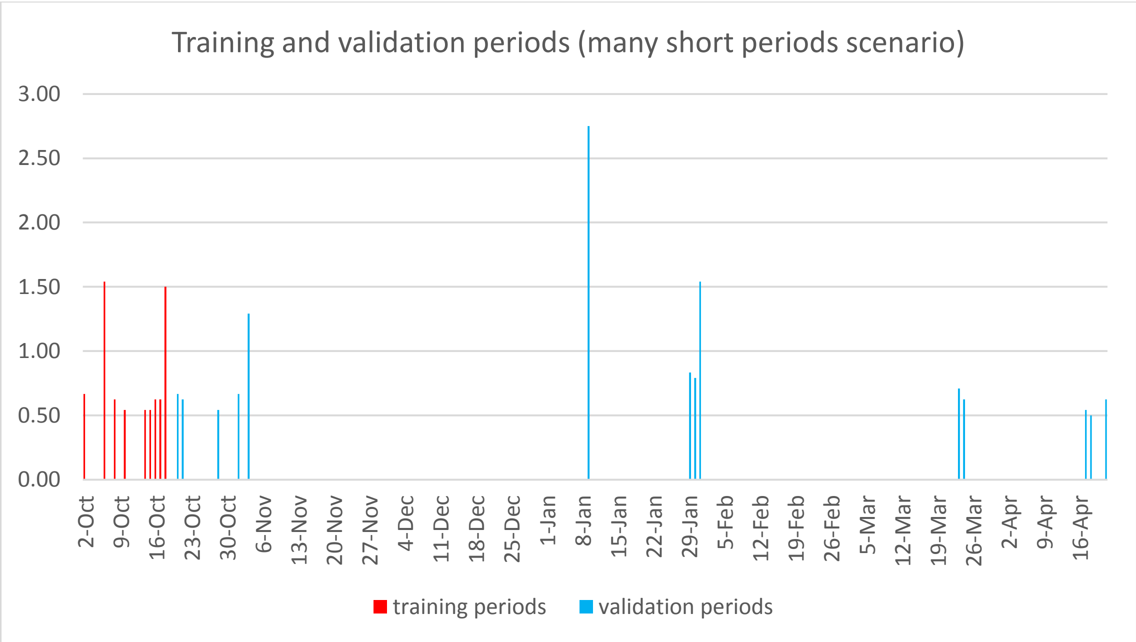


Fig. 66: Training and validation periods for validating the many short periods scenario with real measurements

	cond (W/m²K)	inf_coef (m³/s/m²)	solar	trans (W/mK)	error (%)
Training model	0.052	4.4 E-05	0.61	1.21	1.6%

Table 13: Training solution (taken as average over training periods calibrated parameters)

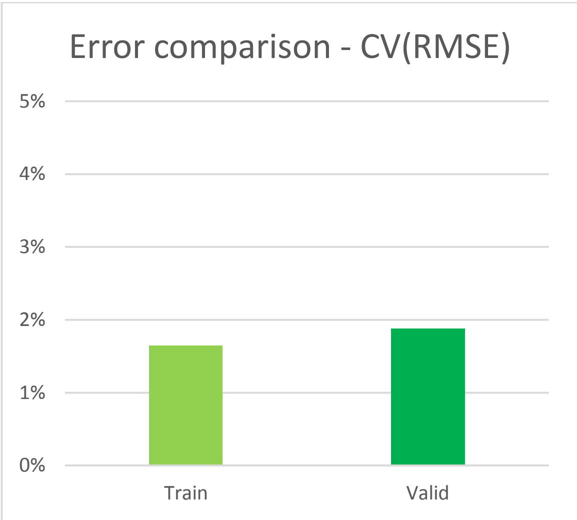


Fig. 67: Error comparison between training data and validation data

Many short periods scenario – Validation results

	MBE (%)	RMSE (°C)	CV(RMSE) (%)
MAX	3.8%	0.7	3.9%
MIN	0.3%	0.1	0.4%
AVERAGE	1.8%	0.3	**1.9%**
STDEV	0.9%	0.2	0.9%

Table 14: Statistical analysis of validation results

It can be observed that the validation error results in 1.9% which is not far from the initial training error of 1.6%. This can imply that the training solution fits the rest of the periods quite well, leading to limited overfitting in the model. Even for the period with the largest error, the RMSE is 0.7°C, thus suggesting that the model can capture the average temperature of the house with relative accuracy.

Validation with 3 random folds

This is performed by separating the periods in random folds of training and validation data. Using the parameters of the training fold, an average solution is derived with a corresponding average training error. Then, this solution is tested against the validation fold, in order to find the validation error there. The distance between these errors can serve as indication for the quality of the solutions of the calibration, with the smallest distance meaning better quality. The number of folds is taken as 3 and the periods are randomly assigned to them in order for all folds to have an equal duration of measured data. The number is selected as the total measured data duration is around 3 weeks, thus each fold is around 1 week long.

2-parameter calibration

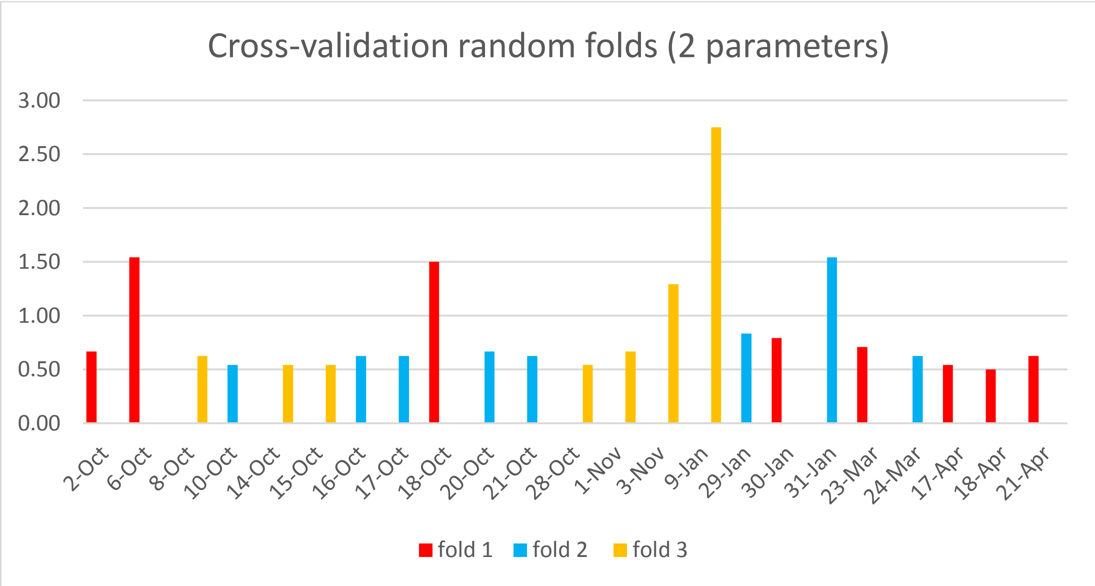


Fig 68: Random folds for calibrating 2 parameters (each of the folds is used to train the model and is validated then with the other two)

Training models	**cond** (W/m^{2}K)	**inf_coef** (m^3/s/m^2)	**error** (%)
Fold 1	0.039	8 E-05	1.4%
Fold 2	0.034	17 E-05	1.7%
Fold 3	0.030	1 E-05	1.3%

Table 15: Training solutions (taken as average over the calibrated parameters of training periods)

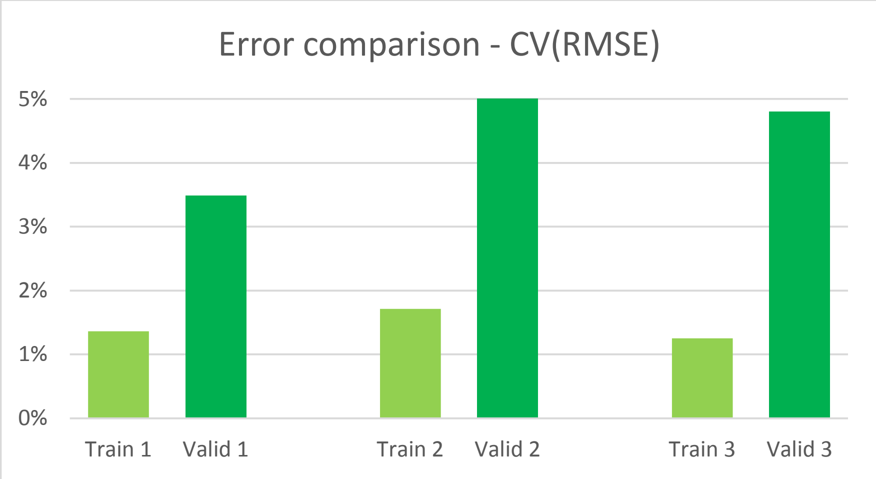


Fig. 69: CV(RMSE) error comparison between training and validation folds (2-parameter run)

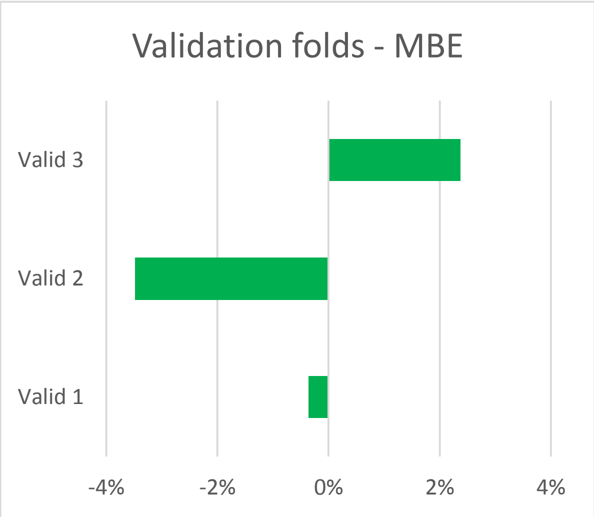


Fig. 70: MBE of validation folds (2-parameter run)

It can be observed that the CV(RMSE) errors in the training solutions are around 1-2% while the ones for the validation are around 3-5%, implying some possible overfitting of the training model, far more than the one found in the successive solution. In the MBE diagram it can be seen that the fold solutions lead to temperature curves that are both under and above the measured data, while the first solution seems to be quite balanced, possible due to the cancellation effect. Also, it can be noted that the third solution seems over-conservative (cond = 0.030, infil=0.00001) and is validated as such, as the MBE is positive and of substantial size, while the second solution is the exact opposite, mainly due to the large infiltration coefficient.

4-parameter calibration

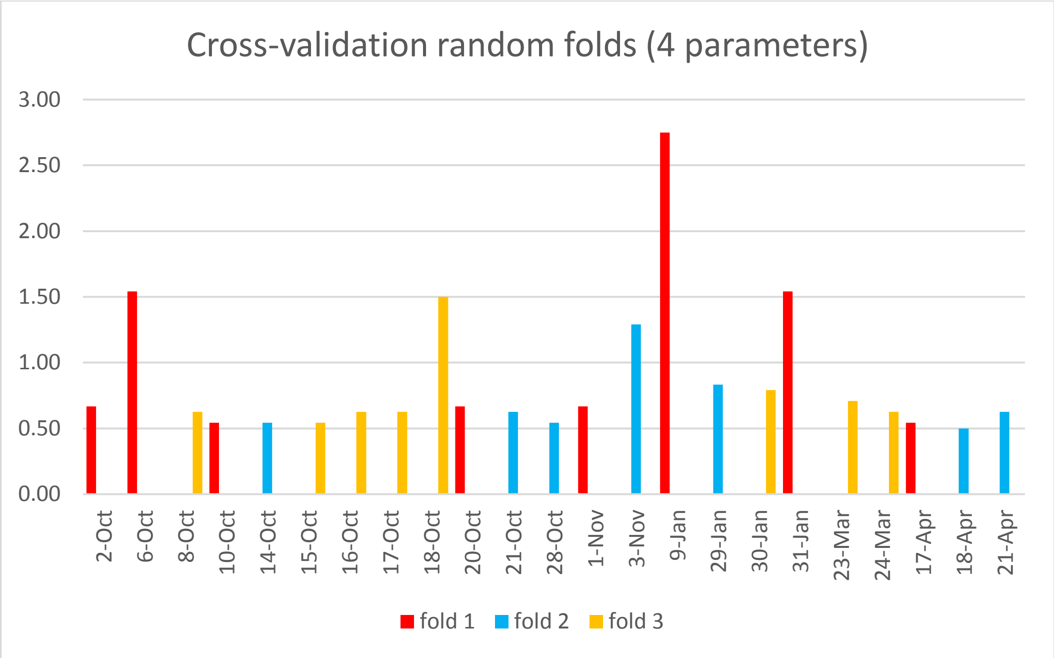


FIg. 71: Random folds for calibrating 4 parameters (each of the folds is used to train the model and is validated then with the other two)

Training models	**cond** (W/m²K)	**inf_coef** (m³/s/m²)	**solar**	**trans** (W/mK)	**error** (%)
Fold 1	0.057	4 E-05	0.58	1.30	0.7%
Fold 1	0.044	13 E-05	0.67	1.76	1.5%
Fold 1	0.051	4 E-05	0.62	1.07	1.0 %

Table 16: Training solutions (taken as average over the calibrated parameters of training periods)

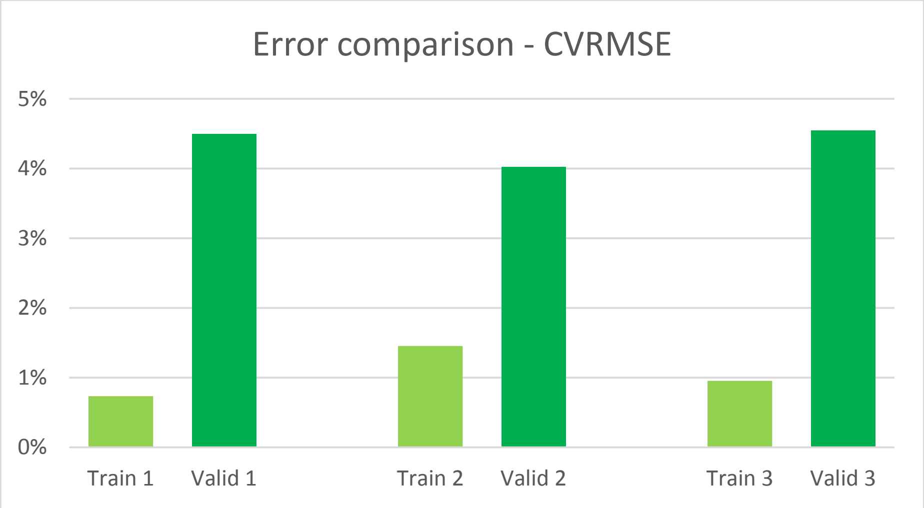


Fig. 72: CV(RMSE) error comparison between training and validation folds (4-parameter run)

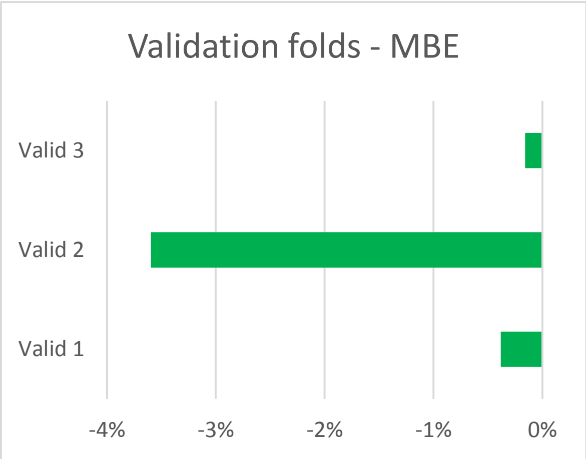


Fig. 73: MBE of validation folds (4-parameter run)

Here the training solution errors are around 0.7-1.5% while the validations are around 4-5% again. This difference might be coincidental due to the different selection of folds, but nonetheless the training and validation have a similar distance as before, implying again that the quality of the results can be sufficient. Nevertheless, all solutions seem to be conservative, as the MBE for all of them is negative, especially for the second fold with a value of -3.6%. That could be suspected as the infiltration rate of this solution is around 13 E-05, quite higher from the calibration average. The same could be seen for fold 2 in the 2-parameter calibration before, where an even higher value of 17 E-05 existed in the training solution.

7. Discussion

In this following the results from the previous chapter will be discussed in more detail and in combination with each other in order to provide some more insight and derive possible conclusions.

7.1 Sensitivity analysis – Size study

From the size study it seems that there is significant difference in the error range by using different time durations and also by having a “close” solution and a “far” solution. The pattern in the amount of time needed to have the highest error is seemingly the same, as error rises in the beginning until some point where the interior temperature is closely following the exterior and then is reduced. In the examined case, this point was around 14 days after the beginning. Nevertheless, this might be possibly due to the design values used and the specific case study. That is, if measured data from a house with less efficient building envelope is used, the interior temperature will reach faster the equilibrium with the external. The effect on this can be the subject of additional research.

The study also implies that for a free flow study, by taking long measurements the calibration quality is not always improving. Also, that there is still some error even in the smallest time duration (12 hours), to be captured in the parameter calibration, although the quality improves significantly for some days or a week, especially when the measured and simulation are not far from each other. That suggests that when the difference between the measured and simulated parameters is becoming smaller, larger durations are needed in order to be able to have enough error for the calibration to work.

Taking into account the physical characteristics of the parameters and the way that the simulation program works, it would be preferable to use a variety of weather conditions, with wind, sun and temperature changes. It is thus assumed, that if this variety is captured by many small durations instead of one large, the calibration quality will not suffer, provided that the convergence limit will be adjusted on the duration size (e.g. for 1 day it would quite small, close to 1%).

7.2 Sensitivity analysis - Parameters

From the results of this analysis, it is indicated that the infiltration coefficient is the most influential parameter with the conductivity of the opaque envelope, solar gains and the transparent envelope U-values to follow. The influence refers both to heat losses and to CV(RMSE) error in temperatures. The infiltration exponent is having a minor effect on both the energy and the error and thus it is not taken into account in the calibration.

Specifically on the error, the influence of the conductivity and U-values is rather limited, for the typical values assumed for an efficient building envelope such as of the Pal House. That leads to a broad estimation for the value range for this parameter, which for conductivity is around 0.4-0.6 and for the U-values 1-2. Such a small influence for especially the transparent building envelope is not very common, as its properties are usually very decisive. The reason might be that in building components with such level of efficiency, the infiltration between their interfaces is becoming the largest heat loss route, leading to lowering of temperature in faster rate than lost by conductivity through the windows.

7.3 Design verification

First of all, it can be observed from the results that the design values are not seemingly giving a very significant error, as on average they are around 4-5% and per area can reach 7.2%. Nevertheless, as is shown in sensitivity analysis, these error ranges can possibly suggest large difference in the parameters, especially for the conductivity and the flow coefficient. Also, the small magnitude of the error might be a result of the measured data size, which is on average between 12 hours and a day. As seen in the data size study, these durations lead in general to small errors, especially when the difference between simulated and the real parameters are not far. Again from the sensitivity analysis, there is an indication that the very low infiltration coefficient assumed from the passive house standard might be a possible the culprit. A difference in even one order of magnitude could result to such high error.

A possible validation of these errors can be the following thermal pictures of the house exterior and interior. These were taken with an IR camera in a very cold day (interior-exterior difference around 25°C) in order to get an indication of the temperature distribution in the house and subsequently, where most thermal losses occur.

Fig. 74: House exterior IR image

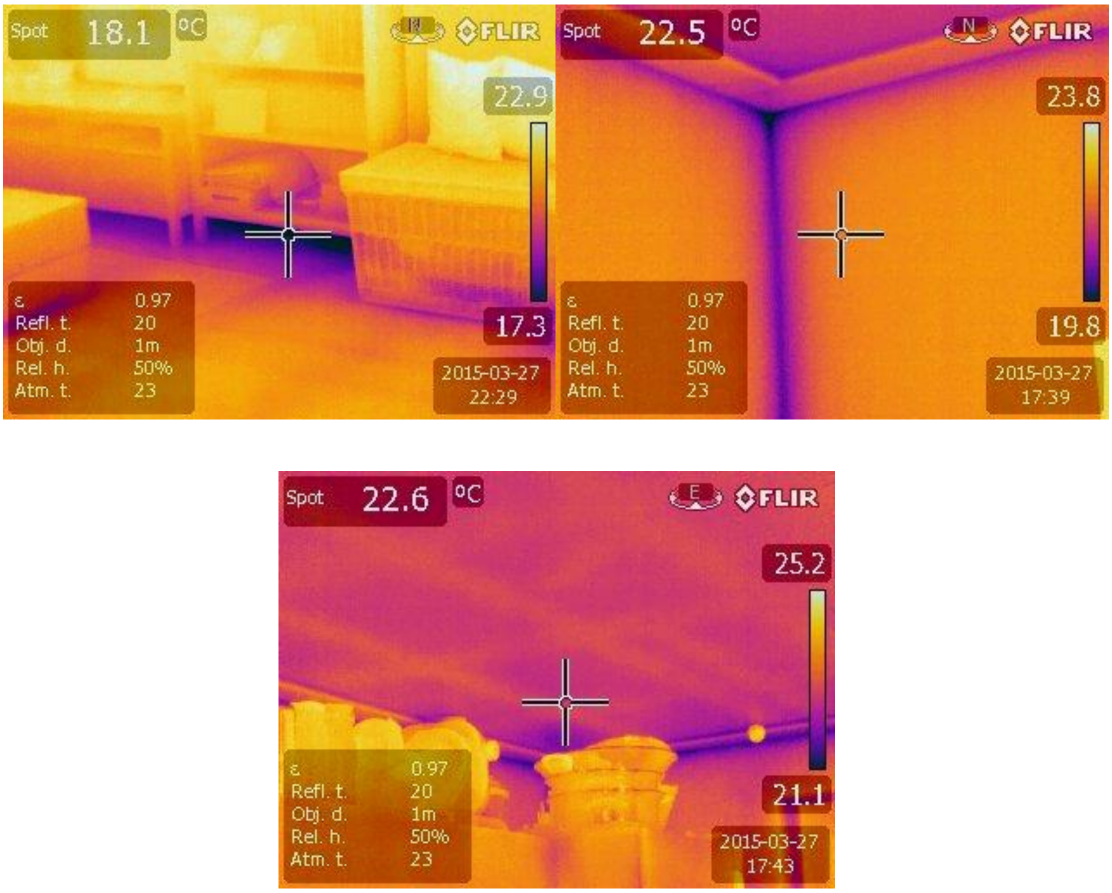


Fig. 75: Living room infrared images

Fig. 76: Front door corridor infrared image

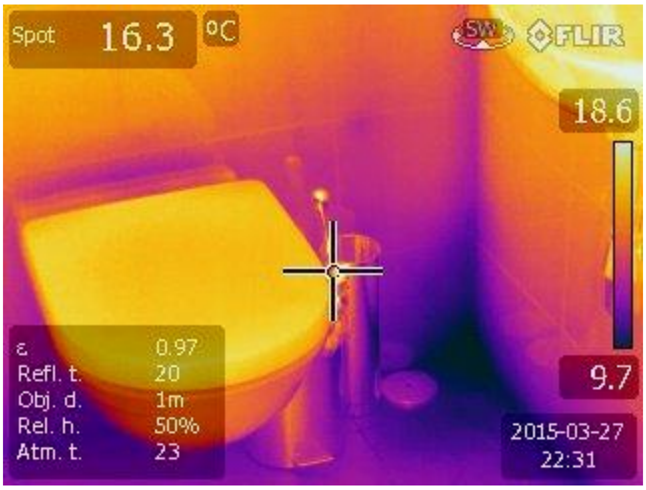


Fig. 77: Bathroom infrared image

It is clear that in all spaces there can be seen areas with lower temperature than the rest of the room, implying thermal bridging effects or infiltration cracks. Based on the construction method of the building, the latter is highly probably as the house was constructed with separate panels for each wall, floor and roof that fitted together and then sealed as best as possible.- Nevertheless, taking into account that the house was constructed 3 times and de-constructed 2 times, it is reasonable to expect that the interface between the elements would become quite rough from damages and bents, leading thus to large cracks that cannot be easily sealed. Some very large can be found in a corner in the bathroom and under the front door in the corridor, as seen by the very large temperature difference in these spots (almost 10°C). In the living room these areas can be found as well, but with weaker effects, as shown from the temperature distributions there.

It has to be noted that these zones were also found to have the largest error by the multi-zone model. Therefore it could give an indication that this type of modelling can help find these zones, although a thermal camera is probably more appropriate. That is, because even if these zones coincide, the average MBE error found by the multi-zone model is almost always below zero. This practically suggests that reality is even better than design, which is not very probable as supported from the IR photos. On the other hand, a single zone also makes more sense with its balanced MBE results.

To explain this difference, it can be suggested that the assumptions of a single-zone model might be more realistic than taking into account that all zones are separate. A possible reason for this is that the air transfer between zone is taken as minimal while their effect in reality are probably quite substantial (e.g. through the doors and the interior walls etc.). The other possibility is that the materials of the as-built components offer more insulation than the as-built documentation is mentioning, even with the existence of thermal bridges or infiltration points as found through the thermal camera, which is again not very probable. Nevertheless, as seen from the separate zone temperature diagrams, there is a difference of 1-2 degrees between the zones, although by taking into account the huge living room volume, this difference is not that significant for the total heat losses. Reality is probably between a multi and a single zone model, and maybe closer to single one as it seems.

7.4 Calibration

Both in the 2-parameter and the 4-parameter models, the calibration results can be indicated as satisfying. That is because their average values are not far from the design values and also they are mostly inside the estimated ranges from the sensitivity analysis as seen from the table below. It is noted that the CV(RMSE) for the calibration average solutions is calculated by validating the resulting model against all measured periods (and not just averaging their errors), in order to be comparable with the error in the design values.

Nevertheless, as shown in the validation chapter, the solution deriving from the successive small measurements scenario is achieving the smallest validation error, suggesting that is a more appropriate solution with less overfitting danger than just averaging all the possible calibration sets.

Parameter set comparison

	cond (W/m^{2}K)	**inf_coef** (m^3/s/m^2)	**solar**	**trans** (W/mK)	**CV(RMSE) validation error** (%)
Design values	0.039	1.0 E-05	0.4	1.30	4%
Sensitivity analysis - max	0.060	10.0 E-05	0.5	2.00	-
Sensitivity analysis - min	0.040	1.0 E-05	0.3	1.00	-
2-parameter calibration - average	0.035	9.0 E-05	-	-	4%
4-parameter calibration - average	0.051	7.0 E-05	0.62	1.39	4.3%
Validated scenario solution	**0.052**	**4.4 E-05**	**0.61**	**1.21**	**1.9%**

Table 17: Parameter set total comparison

For the opaque envelope conductivity, the 2-parameter calibration yields an average value lower than the design value while the 4-parameter does the opposite. The values are not very far from each other and due to the small influence of conductivity on the error and the large standard deviations, it seems that a convergence on an extremely limited value range is not possible for this parameter.

On the contrary, the infiltration coefficient is very close in both the calibrations and with smaller standard deviations. If it is also taken into account that is the most influential parameter found in the sensitivity analysis, it can be suggested that the calibration can better converge on it. This is also assisted by the fact that is the only parameter using the atmospheric pressure and wind speed climate input, in comparison with the conductivity and U-values that use only the temperature difference exterior-interior. Also the calibration results of 4 E-05 to 9 E-05 are in agreement with the thermal images, as a higher infiltration rate than the designed was more than expected.

As for the transparent envelope U-values, the calibration manages to find a value very close to the design value. This design value has a higher confidence level than the opaque envelope conductivities and the infiltration, as the windows are having better quality control and undergo stricter tests.

Finally, the solar gain coefficient has a large distance from design value although it is also having a quite high confidence level. It is also outside of the range found by the sensitivity analysis. An attempted explanation might include coupling effects with the conductivity in the 4-parameter calibration, as it is also quite high. Since a high solar gain leads to heat gains, some of the larger heat losses from the higher conductivity might have been negated, reaching an equilibrium between them. It is suggested that with more measured data with climatic variety, a better estimation would have been made. That is because the solar gains could be more influential as the climate characteristic that affects them and only them is the solar irradiation. An indication for this suggestion is given on the validation of the calibration method where a week of data with high climatic variety is used.

7.5 Validation of calibration process with known parameters

From the shown tests with random data it can be derived that the calibration algorithm can find the target values with significant accuracy, for both the use case scenarios specified. It is noted however that high quality measured data is used, with large duration, climatic variety and most importantly, no hidden disturbances, as it was create by an initial simulation. Also, it is apparent that statistical analysis is necessary in order to extract useful results, as only one solution derived from a stochastic method such as this does not bear enough reliability, even if the convergence limits are small. The research for defining this statistical analysis goes beyond the scope of this thesis but can be a recommended follow-up. From the initial study performed here, there is an indication that the method can find the most important parameters of conductivity and infiltration with great accuracy.

Also, it is shown that a multi-parameter model is not appropriate for the calibration process as its values couple with each other and miss the target values. Also, it makes things more complex without an apparent need, as for finding the total heat losses of a zone, a lumped mass model with average conductivity and area can be used with accuracy.

Finally, it is shown that the time needed for the calibrations can be quite high, depending mostly on the population and the generations or on convergence limit, while the time for running one analysis remains constant on around 2.4secs. It is also pointed out that runs with hundreds of generations did not result in notably better convergence.

7.6 Validation of calibration with live measurements

From validating the scenario of successive many short periods a solution is derived with limited validation error and limited overfitting. As observed for the calibration with known parameters, it can be thus assumed that the found solution set is quite close to the real parameters. For the random fold validation, the overfitting was more significant with a training error of around 0.7-2% while the validation is on 4-5%. Thus a difference of 2-3% in comparison with the 0.3% difference of the successive training scenario. The 2-parameter calibration is found to be slightly more accurate, due to the more balanced MBE, in comparison with the 4-parameter calibration where all the curves of the training solutions were lower than the measured data.

7.7 Overall

In general it can be said that the targets set from the research proposal and questions have been achieved to a large extend. The verification process can possibly provide new houses with a quantifiable indication of whether the parameters from the design documentation are accurate in the reality. This can help to improve the quality of construction by assuring that the as-built situation is having similar behaviour with the design simulation. Thus possible corrections can be made for assuring that the operational energy in the future stays in the levels calculated in the design. Also, it was shown that a single-zone model can be even more accurate than a multi-zone one, suggesting that one temperature validation point in the center of the house is enough, provided that air exchange between all the rooms is not significantly blocked.

On the other hand, calibration can provide a more justified specification of the properties of a building rather than just choosing based on e.g. building year etc. From the results it seems that it can provide a quite accurate range of values, especially for the most influential parameters for the heat losses estimation. For the other parameters, the range might be larger but the effect on the energy is not that important, leading to similar heat losses. Thus, it can possibly provide a better estimation of them during the year, by taking into account the local conditions and inconsistencies of the specific building and lead to a better understanding of its real behaviour. This can then be used for predicting with more accuracy the future energy needs and for setting up policy targets.

From the results of the sensitivity analysis it is derived that the method may be more effective for houses with poor building envelope, as the error would be larger and the calibration quality higher. Also, small durations of measurements in the scale of a week, a day or even 12 hours can be used, provided that there is enough climatic variety and that the expected error convergence is adjusted accordingly. Many small measurement durations with a total sum of a week are seemingly enough for calibrating the specific case study (with two weeks being optimal). Also, for the specific case study the infiltration coefficient is the most influential parameter, as expected for passive house level buildings.

Finally, it has to be noted that results might be possibly case-affected (glasshouse, no thermal mass, 3 times rebuilding etc.) and further research should be made to make sure that these conclusions are valid in general.

8. Conclusions and recommendations

In the following the main conclusions are presented as derived from the results and the discussion before. Also, recommendations for follow-up studies, possible improvements or more detailed research are suggested.

8.1 Conclusions

From the overall discussion in the previous chapter, the following conclusions can be summed up here.

- **PaL House design validation:** It is shown that the design parameter values lead to 4-5% error implying that they differ from reality. More conductive heat losses and more infiltration are expected than suggested from the design documentation.

- **New house verification process:** Coupled with sensitivity analysis, it can provide a quantifiable indication of how efficiently the design is translated to the real construction, in terms of space heating requirements.

- **Old house calibration process:** It can result in accurate sets of parameter values based on the real space heating requirements of the building. The process is tested successfully against known parameters and validated for the PaL House measurements with small resulting error (1.9%) and overfitting (0.3%).

- **Model type:** For the terraced house typology, the single-zone model seems more accurate than multi-zone, possibly due to the extensive air and heat transfer between the rooms.

- **Measured period:** Sufficient climatic variety should be used. It is also depending on house building envelope efficiency – for very efficient 14 days seems optimal.

- **Most important parameter:** Infiltration rate (for the specific case study).

It can be noted that the comparison between the estimated consumption of the house with calibrated parameters and the actual measured energy is avoided here. The reason for this is that even with the assumed improvement in input parameters for space heating, the real energy consumption is depending on many other parameters, e.g. from the thermostat set-point and mechanical equipment efficiency to the user behaviour and the average electricity used for appliances. To be able to have a valid comparison, these parameters should also be added to the model in detail although there is no monitoring information for them at all times. As analysed extensively in Chapter 2, the focus of this study was on creating the basis for calculating its yearly consumption and not on comparing this energy in simulation and reality. Nevertheless, since the calibrated solution leads to small error, it can be assumed that the heat losses in the model and in reality are not far from each other.

Conclusions on reusability

It can be mentioned that in the way these processes have been developed, the re-usability on other terraced houses is strongly implied. Since the PaL House was built to represent this typology as close as possible, it can be assumed that calibration or the validation process would work in the same way as here. From the findings of this study, the following applied process could be used:

1. Take measured data from an old, new or refurbished house
2. Install one temperature sensor in the middle of the house (living room)
3. Collect max 14 days of measured data
4. Apply processes, parameter validation or calibration
5. With these parameters and some statistics on the specific user behaviour, thermostat set-point etc., calculate the space heating requirement
6. By taking into account also the electricity used for appliances etc. calculate the total energy consumption for a year.

8.2 Recommendations

Through the course of this thesis it was found that there is a large amount of opportunities by coupling measured data and simulations. Focusing in thermal losses as it was done here is one of them, but there are more possibilities to improve or scale the whole process. Also, there are possibilities of studying different aspects, such as the efficiency of the mechanical equipment of a house, or the thermal comfort or even study a different typology. A selection of these recommendations can be found below.

- More and larger design periods should be tested and with a more “regular” house. The effect of thermal mass on the method is also very important.
- Experiment with duration or season on the validation of the calibration method itself.
- Stronger comparison with Energy label predictions by using an existing house that has been already inspected and assigned an Energy label.
- A similar process can be devised for configuring and verifying the new installations in a newly refurbished dwelling and make sure that everything was constructed and operating as designed.
- Explore the connection of heat losses and possible disturbances, e.g. internal loads, natural ventilation losses etc. A possible way to do so is to add this extra energy factors to the calibration unknown parameters. It can then be used to find out the noise on “known” conditions and thus create known situations (e.g. find the correlation between energy use and actions on a normally used house). This parameter can be also in the form of a polynomial in order to approach the curve of the effect of these actions in a more accurate way.
- Explore the possibility of using a sensitivity analysis automatically coupled with the calibration in order to iteratively limit the search space.

9. Appendix

9.1 Background research

Energy refurbishment

Working with existing buildings, i.e. without the nearly empty canvas of a new building design, can prove a complicated challenge. This can be further illustrated by the many different types of existing building works that usually have variable definitions depending on the country of origin, sub-sector, and stakeholder of each project. As with renovation, conversion, maintenance and other types, it is difficult to specifically define refurbishment and its extent.

Giebeler et al (2009) offer a possible definition to them based on their relevant intervention on specific components. Thus renovation causes no major change to the main building components of the house but is mainly an "upkeep", including painting or the treatment of external surfaces. On the other hand, conversion affects deeply many components as well as the main structural system of the building. Refurbishment is somewhere in the middle, where damaged or outdated components are replaced but the main structural system is kept intact.

Following the same principles but with a more specific goal, energy refurbishment can be briefly described as "a package of measures to upgrade the energy efficiency of an existing building" (Hall et al., 2013). These measures usually follow the basic sustainable design philosophy of the 3 R's, i.e. Reduce, Reuse, Recycle, adjusted for the energy use in buildings.

In Netherlands, relevant research shows that the three highest energy uses in the energy bills in housing are:

3. Space heating
4. Home appliances
5. Domestic hot water

From the statistics of domestic energy consumption in 2011 in Netherlands, an average annual consumption of 1,617 m^3 of gas and 3,480 kWh of electricity is derived (Energiezaak et al., 2011). Nevertheless, the distribution of each use is not uniform, as can be observed in the diagram below. Most notably, central heating is reaching

34% of the total energy use in housing, rendering it one of most important consumption factors to be reduced.

Fig. 78: Breakdown of energy bill by use (Energiezaak et al., 2011)

Subsequently, most of the refurbishment measures are focusing on reducing the energy needed for space heating by intervening on house components or substituting the existing installations with new and efficient ones. The most important of these components as suggested by Magrini et al (2014) are:

- Opaque building envelope (e.g. insulate walls to reduce thermal losses)
- Transparent structures (e.g. replace inefficient windows with HR++)
- Space and water heating systems (e.g. replace old boiler with efficient heat pump, install solar water heating).

Documenting the existing

The focus on “packaging” the measures is significant. As market and designer experience is showing, individual refurbishment measures (e.g. just insulate the walls or just install a heat pump) are not solving efficiently the problems of these houses. Instead a combination of them should be proposed by the designer according to the specific existing house at hand. This suggests that the designer should capture in his initial analysis and energy performance assessment the reality of the existing, as detailed as possible.

This documentation of reality can be broken down to the following sub-sections:

- Microclimate of the area
- Geometrical characteristics
- Material characteristics
- Localities (damages, moisture problems, thermal bridges)
- Installations
- Profile and schedule of use by the tenants

If these sub-sections are even further analysed, the designer ends up with an overwhelming amount of parameters that should be carefully derived from the existing building. It is noted that the most typical source of information is the real building itself, as usually the old design specifications and the construction plans are incomplete or even missing altogether. Thus it is evident that a clear analysis would require a “sea of data” from the existing building that the designer should create.

This *data problem* can be suggested as one of the reasons why integrated, custom-based solutions for refurbishment are not widely used by the market and the designers. Additionally, the financial and collaboration particularities of the AEC as well as the traditional inertia of the sector to changes are further reasons preventing the fast development of these solutions.

The usual refurbishment procedure in the Netherlands

One example to illustrate the above slow and out-dated procedure of refurbishment design comes from the residential sector of Netherlands. It is loosely based on interviews to relevant professionals as well as the experience of one of the aforementioned researchers, T. Konstantinou (2014):

1. A housing company calls an architect to estimate a refurbishment solution.
2. Typical refurbishment target: Raise the house Energy Label to B
3. It is specified as an agreement between housing companies

4. It can result to a higher rent.
5. (It is noted that the housing Energy Labels in the Netherlands are specified by an energy index, loosely based on the architectural characteristics of the houses as well as the efficiency of their installations and not so much in definite metrics such as the final electricity or gas use etc.)
6. The architect identifies some potential problems comes to solutions using a simple AutoCAD floor plan and some data from a first level audit. Does not have/use much custom design information. It is based on experience and intuition.
7. (optional) The architect contacts a building physics specialist to confirm with simple models his design.
8. Hands in the results to the housing company that estimates the cost by using simplified models/experience or maintenance expert companies.
9. The housing company proceeds then to tendering and the main design, following usually what was decided in the pre-design phase.

The above suggests that the typical procedure is not taking into account the real energy performance of the specific house and the magnitude of its weak points. Instead it uses standardized general solutions to solve in a general and flat way all of the possible problems. Thus it is difficult to assess the apparent efficiency of each energy refurbishment without accurate knowledge of the existing and the updated situation. This also reflects on the financial and investment side of the refurbishment as the amount of energy efficiency and comfort that can be “purchased” with some specific measures becomes unclear.

Row house typology

For the typology of the row houses, it can be argued that the general material properties, construction details and usual problematic areas are already known and documented in relevant publications and they can be visually confirmed by a fast inspection. Furthermore, the energy use can be derived from the gas and electricity bill and thus base the refurbishment solution in projected reductions of these numbers.

Nevertheless, these houses have still some significant unknown factors:

- Thermal bridging properties, which are depending on the exact construction details, materials and localities (damages etc.)
- Natural ventilation schedules, as most of the houses depend in natural ventilation for air renewal and this depends on the room allocation, number of users, their preferences etc.

These factors can lead to an obscured image about the comfort conditions in these houses. Thus, they can undermine one of the reasons for the refurbishment which is to improve the comfort, by rendering the quantification of this improvement virtually impossible. Additionally, variations in material properties, hidden construction details and damages in the components or on layers (e.g. in the insulation) can also lead to a non-accurate view on the weak spots of the house that need to be addressed. From the above estimations, thermal bridges seem to present one of the biggest challenges due to the variation of their impact to the energy performance of the house and thus they are further researched in the next.

Thermal bridges

A general definition of a thermal bridge is offered in an educational context from Szikra (2010):

<<A thermal bridge is a component, or assembly of components, in a building envelope through which heat is transferred at a substantially higher rate than through the surrounding envelope area, while also temperature is substantially different from the surrounding envelope area.>>

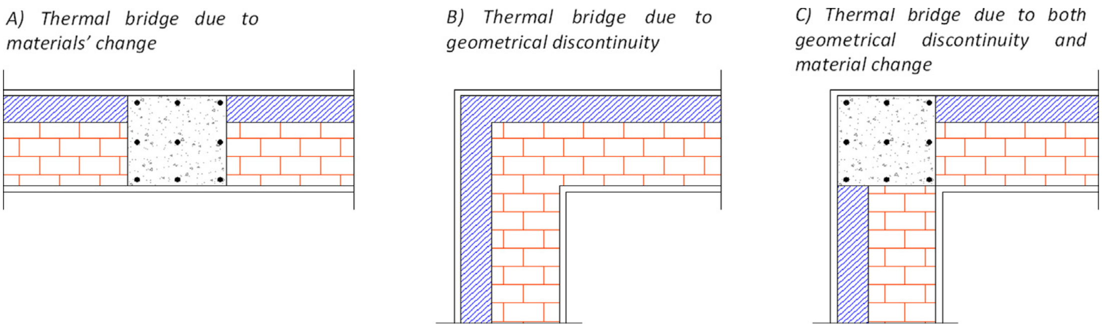


Fig. 79: Typical typologies of thermal bridges in buildings (Ascione et al., 2012)

Their relative impact on the heating energy estimation can be as high as 30% in European Member States (Citterio, 2008) depending nevertheless on many factors, some of them mentioned before. The most important tends to be the existence of adequate insulation in the surrounding envelope area as e.g. in a non-insulated wall the heat loss from the envelope is practically uniform and the impact of the thermal bridges lower and the other way around. The variation of impact can be in general less than 20% in the non-insulated situation and more than 30% in the insulated (Szikra, 2010) while a specific research on Czech housing (Citterio, 2008) shows a 7% impact for houses constructed in the 70s and 28% in modern constructions.

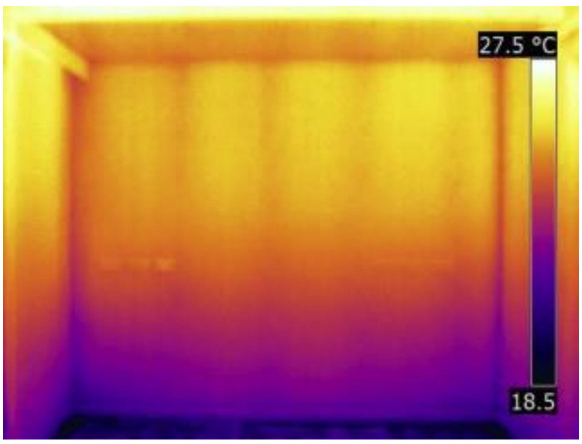


Fig. 80: Thermal bridge effect in the corners
and in vertical components (Taylor et al., 2014)

For the row houses of the Netherlands, the above variations can be taken as relevant, with an offset of some years considering the advanced construction tradition of the country and the early introduction of insulation. As shown in figure 17 most of the houses in the Netherlands have double-glazing windows while more than 60% of them features also insulation in the roof and the walls. The rest of un-insulated houses are apparently coming from older post-war typology. Nevertheless, even if the construction year of the house offers a possible indication of the existence and even the type of insulation, its current efficiency and integrity can be considered doubtable. Especially if one considers damages, construction defects, the lifetime of the material and possible partial refurbishments in the past, it is becoming evident that a correct assessment of the impact of thermal bridges in an existing house is not easy.

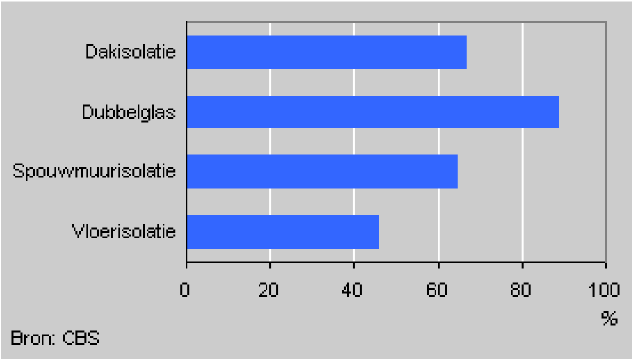


Fig. 81: Thermal insulation types in housing Top to bottom: Roof insulation, Double glass, Wall insulation, Floor insulation (CBS Centraal Bureau voor de Statistiek (NL), 2004)

In the normative context, thermal bridges in Europe are usually assessed for new structures and not in refurbishments (Citterio, 2008), thus most of the calculation methodologies are focusing there. Some examples are suggested in the EN ISO 14683 (2007), with numerical calculations of 2D and 3D heat flows (e.g. with finite elements) being the most accurate (±5%) and with default-standardized values of thermal losses per bridge type being the least accurate (±50%). On the other hand, there are a lot of methods to identify existing thermal bridges such as thermography, sensors and 3D thermal modelling, as summarized by Vidas and Moghadam (2013). Nevertheless, most of them require specialized and expensive equipment and they don't provide easily a clear impact metric that could be aggregated with the rest of the energy performance factors.

Therefore it can be observed that even in a simple typology such as the row houses, thermal bridges present a multi-parametric problem that depends in the local and current conditions of each existing house. Unfortunately, apart from this problem for the existing buildings, there is further complication regarding the aforementioned integration of thermal bridges with the typical building performance assessment methods. This is discussed in extend below, after a general introduction to one of these methods and specifically, the Building Performance Simulation.

Building Performance Simulation (BPS)

It is currently one of the most usual methods for calculating building energy performance, especially with the level of computational power that the current computer systems can harness. As summarized by Coakley et al. (2014), they are tools that allow the detailed calculation of energy flows in the whole building, under the influence of external factors such as weather, user occupancy or infiltration through cracks etc. The calculation is mainly performed by solving heat-balance differential equations at discrete time steps for parts of the building called zones. For defining the characteristics of these zones, a large quantity of data is required to fully describe the physical properties of the building components and installations as well as the dynamic external inputs such as the weather (provided by standardized weather station measurements or custom monitored data). Their results are usually including building information about the energy consumption, comfort conditions, day-lighting etc. for a selected time span (hours, days, months, years). Finally, one of the main advantages in BPS methods (in comparison with mathematical or statistical methods) is the ability to predict building energy performance also in the future, offering possibilities for the operational optimization of the building (Coakley et al., 2014).

One of most established tools for BPS is EnergyPlus, an open-source program provided by the US Department of Energy with a long history of use and development. According to its documentation (Energyplus, 2013), the program is an energy analysis and thermal load simulation and includes most of the features and processes described above. It can perform both steady-state and dynamic simulation depending on the goal of the designer. One of the things although that EnergyPlus is not including is a user interface, as the program provides the strip-down computation engine and uses a simple ASCII text file for both input and output.

Nevertheless, the program's popularity by the design and research community led to many plug-ins and custom user interfaces, with the most popular being the Openstudio, a cross-platform collection of tools to support whole building energy modelling using EnergyPlus. Lately, a significant addition to support EnergyPlus with an integrated modelling environment with detailed inputs and a variety of results outputs is DesignBuilder. The program creates a full input file of EnergyPlus through a user-friendly environment, including a CAD engine for the geometrical inputs, and then analyses the results through graphs, tables etc.

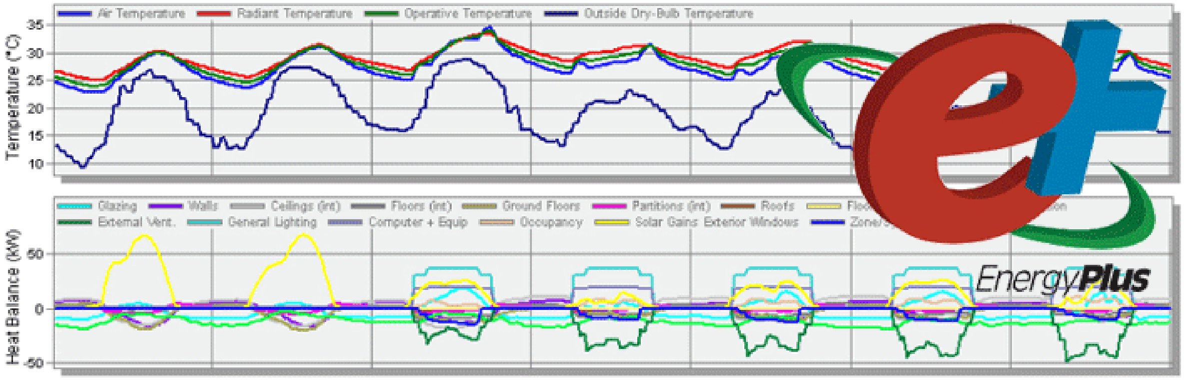


Fig. 82: DesignBuilder output of temperatures and heat balance (DesignBuilder, 2013)

Concerning the inclusion of thermal bridging effect to EnergyPlus, there is fundamental barrier from the program, namely its main computational method. As mentioned before, EnergyPlus is solving heat-balance equations between zones, thus creates a 1D heat flow model to speed up the calculations, especially if these are for an annual simulation with a small time-step. Instead, thermal bridging simulation essentially concerns local instabilities inside the zone that are taken into account by considering 2D and 3D heat flows. The integration of the above types, the global 1D model and the many local 2D-3D models, is a subject of extensive research as reported by Gao et al. (2008) and Ascione et al. (2012). There are many methods developed to surpass this, with varying success and complexity as it is also reported.

One of the most typical methods used is the Equivalent Wall Model (Enermodal Engineering Limited, 2001.) that mainly calibrates of the U-value of the building component to include the thermal bridging effect. A typical variation of this method adjusts the thickness of the insulation layer to achieve the same U-value as of the bridged component. As described in BS EN ISO 6946 (2007) this component takes into account the percentage and the thermal conductivity of the material mostly responsible for the thermal bridges (e.g. metal studs in a composite wall structure).

Still, even this simple method could be difficult to apply in existing housing as this would require detailed geometrical and material knowledge that is difficult to find, as explained above. This problem provides the initiative to consider other possible methods for finding the data needed for an accurate simulation of the existing row houses. One of these methods can be the use of monitored data from the existing building to calibrate the BPS models and which is further discussed below.

Calibration with measured data

The usage of monitored (or empirical) data for the validation of the building performance simulations is a subject studied from the 80s (Judkoff et al., 1983) but continues to be popular in the relevant researching community even today. Numerous methods have been developed and for different reasons and goals as extensively summarized in the recent review by Coakley et al. (2014). Indicatively, one of these methods use evidence-based calibration where the parameter values for the final model are directly referencing sources of real building information by using a version control system. (Raftery et al., 2011). Other methods include sensitivity analysis to assess the influence of some input parameters and then manually calibrate them (Eisenhower and O'Neill, 2012) or statistical approaches through Bayesian calibrations (Heo et al., 2012).

One of the most typical uses of calibration is for building commissioning and practical operational optimization, as mentioned by Claridge in a recent handbook for BPS (Hensen and Lamberts, 2011). In a nutshell, it is about calibrating a BPS model to monitoring data in order to use it as a reference for future optimization of the HVAC functionality of large buildings such as offices, hospitals etc. From the same source it is derived that this reconfiguration of complex HVAC systems can lead to energy savings of up to 30% in USA, without major capital investment (e.g. by changing temperature set-points, schedules in the HVAC operational system etc.).

As it is also mentioned by Heo et al. (2012), one possible goal is the use of calibration to improve the simulation of an existing building for retrofitting/refurbishment. Two terms are used for describing the main processes; *operational adjustments* is referring to the process of finding the observable parameters of the BPS through auditing while *parameter estimation* to the process of estimating the non-observable through iterative and heuristic techniques, such as trial-and-error.

Even if in most of the techniques an iterative process is adopted, almost 74% of them are in fact manual to some extent, thus only a few are using some kind of automatic optimization or mathematical method to achieve convergence (Coakley et al., 2014). The usual metrics to define this convergence is the Mean Bias Error (MBE) showing the mean difference between measured and simulated data points, the Root Mean Square Error (RMSE) showing the variability of the data and the Coefficient of Variation of Root Mean Square Error CV(RMSE)(%) for determining how well a model fits the data. Usually the limits for this convergence are based to the predicted energy consumption and are taken from standards such as the ASHRAE Guideline 14. The most used limits can be seen in Table 1.

Standard/guideline	Monthly criteria (%)		Hourly criteria (%)	
	MBE	CV(RMSE) (monthly)	MBE	CV(RMSE) (hourly)
ASHRAE Guideline 14 (2002)	5	15	10	30
IPMVP (2007)	20	–	5	20
FEMP (2008)	5	15	10	30

Table 18: Acceptance criteria for calibration of BEPS models from different standards (Coakley et al., 2014)

Regarding automatic calibration methods, one of the most appropriate candidates apart from Bayesian calibration would be mathematical optimization. According to the review, it is not one of the most used methods until now but it is suggested that with the current advances in the average computing power it could be further explored. The techniques used for optimization until now include the *penalty function* and the *objective function* in order to reduce the difference between the measured and simulated data by e.g. reducing the likelihood of deviating from the base-case or by minimizing the MBE.

From the above and the relevant recent literature it can be concluded that the field of model calibration is still ongoing, offering many opportunities to solve a variety of problems in the building sector, including the problem of improving the simulation of existing buildings. Nevertheless, one of the major drawbacks is the use of numerous parameters in these models to achieve the required accuracy. As mentioned in general in the literature and here from Coakley et al. (2014):

<<…the calibration of forward building energy performance simulation (BEPS) programs, involving thousands of input parameters, to commonly available building energy data is a highly under-determined problem which yields multiple non-unique solutions>>

Ultimately, this is another reason for focusing on the simple typology of Dutch row houses, as this can provide a significant minimization of the parameter space, a sufficiently accurate estimation of the initial values and an easier identification of the most important parameters.

9.2 Detailed setup – Monitored data

Main source: PaL house monitoring system

The prototype house is currently situated in the campus of TU Delft in Delft, the Netherlands. It serves as an educational and research facility for the university and as an inspiring space for promoting sustainable solutions for the built environment, among the academia and industry. In the context of the first function, the premises, the measured data, the automation and the installation control are made available on demand for researchers of TU Delft to conduct various research on subject as energy conservation measures, user-behaviour study, energy simulations etc.

Nevertheless, it is stressed that due to this multiple function, the use profile of the prototype is not following the typical one for a residential space, although all of its installations and climate systems are meant for this. For example, it is used also for presentations or exhibitions, with the presence of multiple people at the same time and with uncontrolled heating and ventilation conditions. Furthermore, there is no permanent resident in the house to align the condition requirements to her use. Therefore, it is evident that not all of the gathered data can be used for studying the house under the assumption of residential use, and appropriate data filtering is applied, as explained below.

For measuring and managing the use of the many different systems and installations in the house, and for its research purpose, a monitoring system is installed. In a higher level the system includes the following:

- Condition measurements from all the rooms in the house:
    - Temperature
    - Light intensity
    - Motion
- Electrical energy and power metering, for the production from PV panels and for the total house consumption.
- Special measurements from the main rooms in the house (living room/kitchen and main bedroom):
    - Humidity
    - CO2 levels
    - VOC levels
    - Temperature and flow rate measurements from the ventilation system

From these, only the temperature measurements are used for the calibration. If the calibration is extended to other types of parameters, more sensors can be used as verification points. The energy metering could be also used in the case of a conditioned model, where the calibration is usually based on the energy consumption.

The monitoring system sends all this information in an online database specialized in monitoring data and time series. It is called TempoIQ and is also provided with an API interface to allow reading the data programmatically.

Furthermore, the system is coupled with an interactive home automation system (known as “domotica” in the Netherlands) that offers the possibility to the user to manually inspect and control all the following or set it in auto mode with pre-defined settings depending on the schedule of the user (e.g. switch off the heating on the working days from morning till afternoon etc.).

- Control possibilities over the:
  - Glasshouse windows, top and bottom, to open and close
  - Glasshouse sun-shading for its position
  - Heating system using the inputs of temperature in the rooms
  - Ventilation system using moisture and CO2 inputs
- Lights in all the rooms through RF emitters to be able to switch them on and off depending on the detected movement.

The list of the exact devices and sensors used and their most important specifications can be found in the appendix

Other measured data sources

Supplementary to the above, two other sources of measured data are used:

- Monitored data from the competition duration in Versailles
- Measured weather data from the site of KNMI, the meteorological service of the Netherlands

The first source is used for some initial observations between measured and simulated results, which can be found in the appendices. The special competition conditions, the number of people inside the rooms and the almost constant natural ventilation, pose a significant challenge to an accurate simulation. Therefore, it is not used as available data for the calibration process.

The second source is providing important data for the creation of the EnergyPlus weather file. A large part of this required data is not measured in the monitoring system and among it, the parameters for solar irradiation. These parameters are necessary for creating the solar load on the house which is significantly affecting the interior temperature and the amount of heating needed, especially with the addition of the glasshouse. Since the closest position that KNMI data are offered for a meteorological station in Rotterdam airport (less than 10km distance from the current house position) the data derived is considered relatively reliable for use in this calibration case.

Data uncertainty

From the set-up of the monitoring system of the house the following sources of errors can be discussed:

1. Sensor uncertainty: This uncertainty stems from the possible error in the sensor's measurement. Most of the devices and sensors that are connected to the domotica have some average error range that is given by the manufacturer. For the measurement of the temperature the sensor used is a FGMS-001 type/Fibaro, with a max error of ±0.5 °C (Fibaro, 2014).

Fig. 83: Sensor used for temperature, light and motion (Fibaro, 2014)

2. Local disturbances uncertainty: The sources of this uncertainty vary but they can originate from user actions or the use of equipment very close to the sensor. This is limited by the fact that most of the sensors are installed close to the ceiling and in locations that cannot be easily affected by the user. Nevertheless, due to the wireless set-up of most of the sensors, these can be relocated as seen fit to avoid local disturbances or situate them more close to the centre of the room that is the typical calculation point for the simulation.
3. Natural ventilation uncertainty: This uncertainty is one of the most important in the monitoring and the building simulations. There are no easy ways to control in detail how much air is coming in the house through natural ventilation or even from opening and closing doors. Nevertheless, the main source of ventilation in the house is mechanical and fully controlled from the domotica while the

natural inclusion of air is limited as possible by careful control of the openings. Thus the resulting disruption coming from this very short “accidental” ventilation is limited.

It is possible that there might be other sources of errors such as the reliability of the domotica itself, the data-logger, the Database used etc. Nevertheless, their probability is assumed to be much smaller than the one mentioned above.

9.3 Detailed setup – Simulated data

In the following chapter the simulation data and the model used to derive it are explained. In order to clearly illustrate and justify the process used for reaching the model, the chapter is presented in a relevant order. First a description of the high-level process is given, which could also apply in general to residential buildings. Then the sources of the data uncertainty are analysed as well as the assumptions for the specific case study with an estimation of their effect on it. Taking the above into account, a more detailed process is presented and used in order to minimize uncertainty as much as possible. Finally, a mention is given to an important part of the simulation process, which is the creation of the custom weather file.

General process description

The simulated data is derived from the building performance simulation executed by the BPS program EnergyPlus. As mentioned in the background research in Section 9.1, the program is creating a dynamic simulation of the building using a variety of inputs, in order to approximate the conditions, the thermal comfort, the energy used etc. The accuracy of the model is largely depending on the accuracy of the input parameters which they can be subsequently affected by:

- The availability of a measured value or an accurate estimation
- Input errors

The first is one of the goals of this thesis subject, at least on the most influential parameters for the building envelope efficiency. In order to avoid the second and since EnergyPlus is lacking a GUI and a user friendly environment, the program Design Builder is used. The program acts as a wrapper for the computational engine of EnergyPlus, allowing for the modeller to add and check thoroughly the input as well as experiment with the model input by easy modification of the input values.

The main parameter groups that are configured in ab EnergyPlus / DesignBuilder model are:

- Geometry
- Zoning
- Openings
- Material properties
- HVAC specifications
- Use schedules (presence and activity, appliance use, lightning etc.)

The usual resources for creating the simulation are:

- Construction plans
- Product specifications
- Manuals of installations and the home automation system
- On-site audits

In the row-house typology, the limited size of most of the buildings leads to a limited list of these parameters. Nevertheless, the first three sources might become difficult to find, especially for older buildings and since the quality control of the construction is not as strict as other larger typologies.

Geometry assumptions

The geometry of the model is added through creating building blocks of appropriate dimensions. These blocks can be used to create the volumes that correspond to the real ones, for example a rectangular parallelepiped corresponds to the ground floor or to the first floor etc. The roof and the glasshouse are created as blocks from extrusion, by creating first the profile of the block in the GUI and then extruding accordingly. The extruded blocks are then converted to building blocks and zones.

A general suggestion for increasing the speed of a DesignBuilder / EnergyPlus model is to simplify the shapes as much as possible, if it is estimated that the zone volumes will not be modified significantly. That is, because the simpler the shape, the less surfaces will be added to the calculation. Therefore, a conservative simplification of the model is used as seen below. The original shape of the house plan in Fig. 37, with all the recesses and details pinpointed in Fig. 38, is simplified conservatively regarding the zone volumes to the perpendicular shapes of Fig. 39.

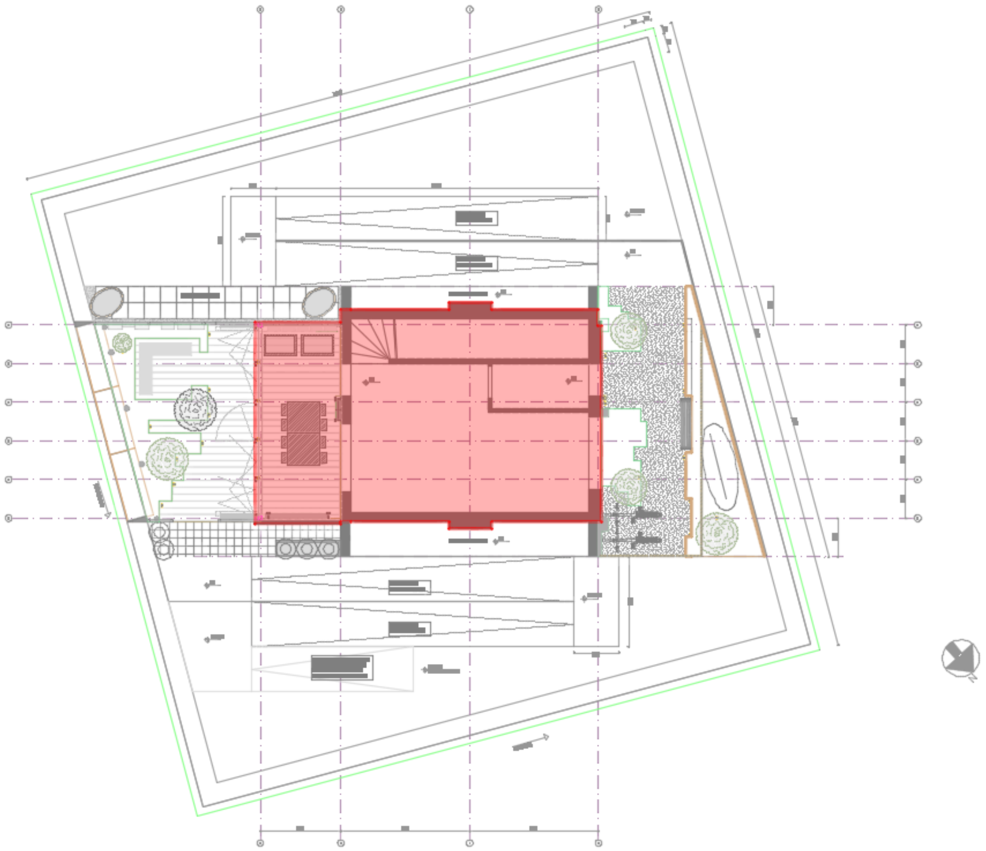


Fig. 84: Original plan shape

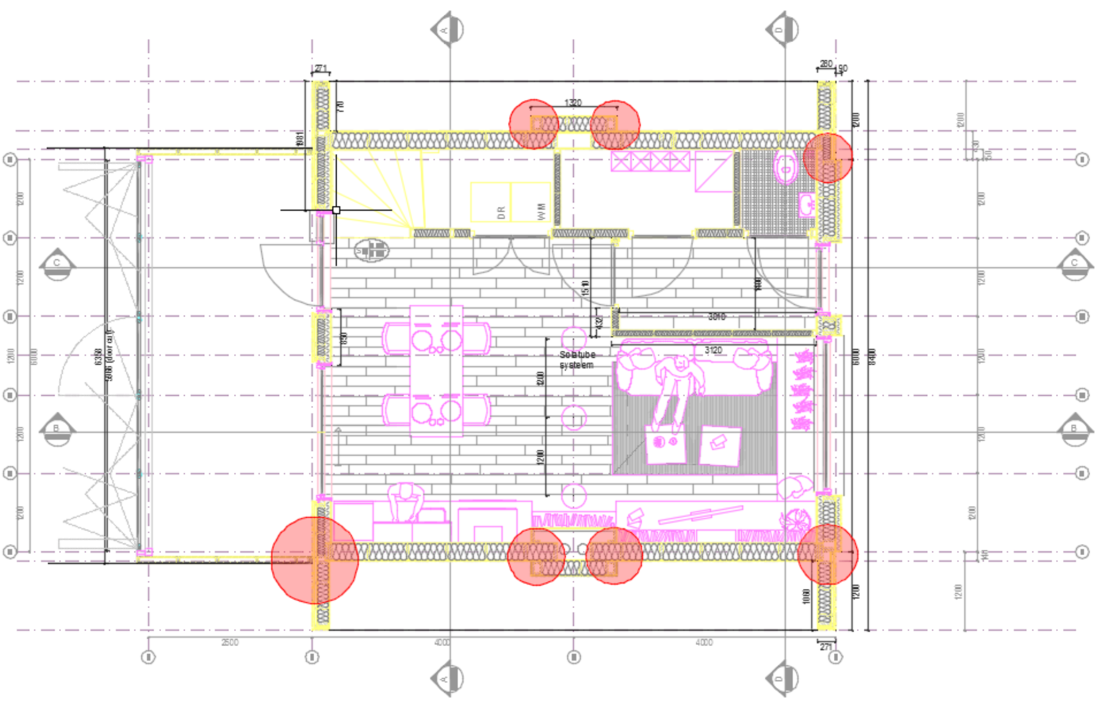


Fig. 85: Details and recesses

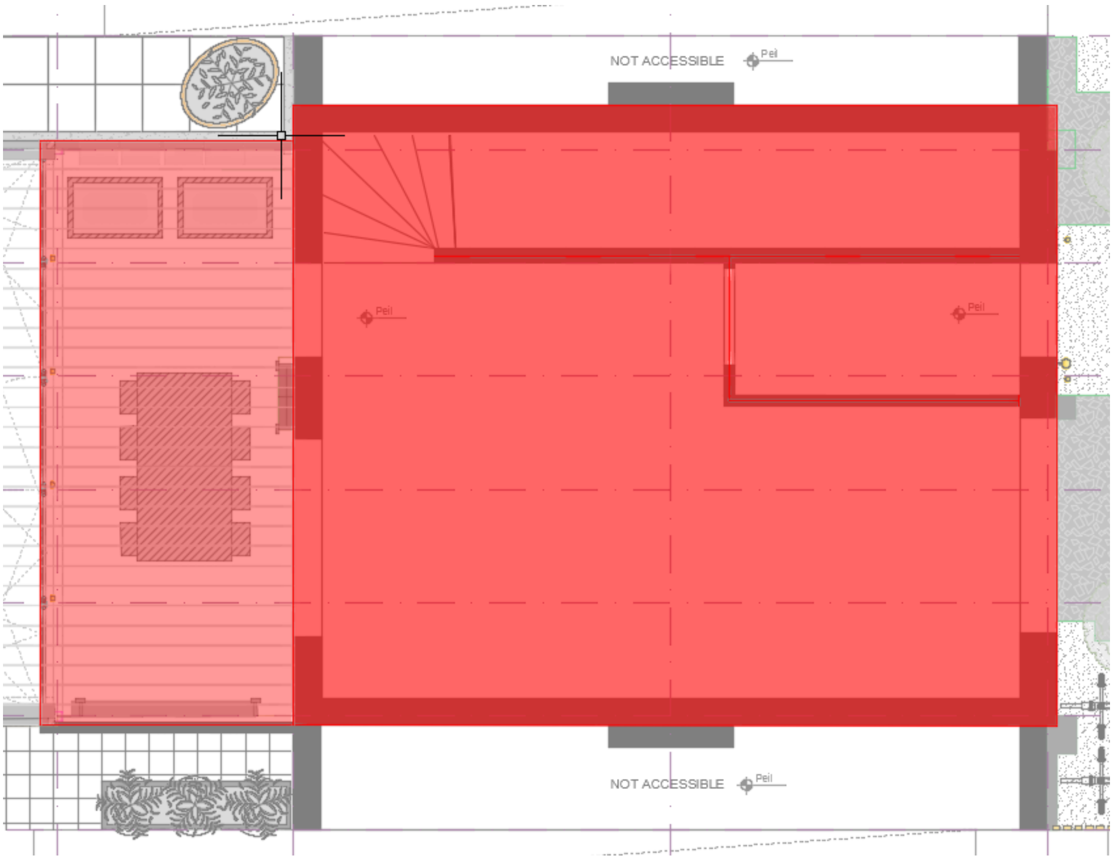


Fig. 86: Simplified model (glasshouse zone on the left, house interior on the right)

The section of house that is used in the model is shown also below:

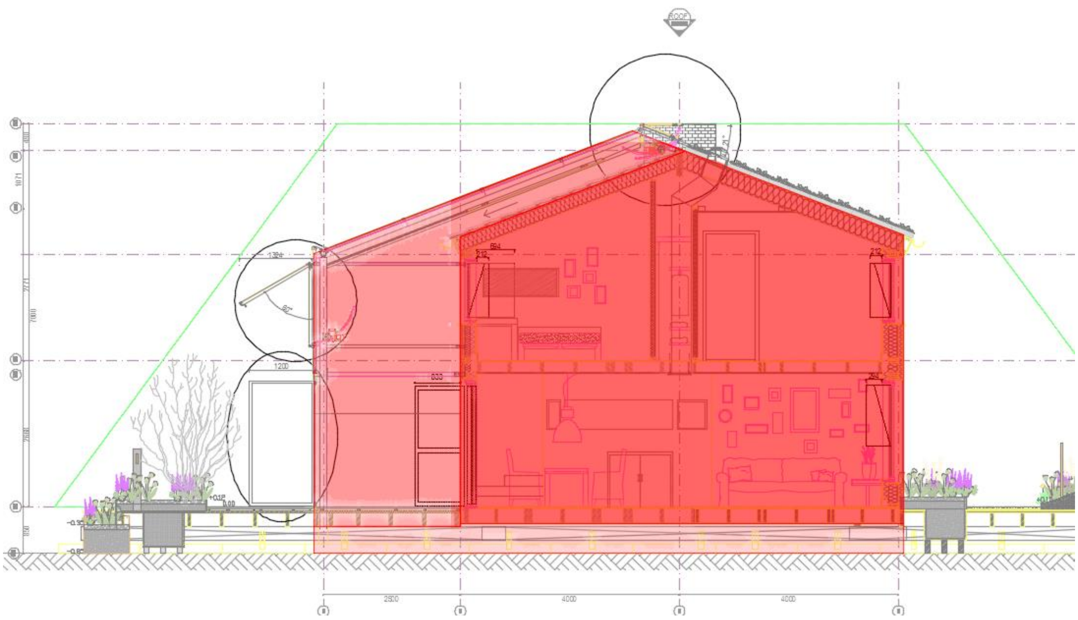


Fig. 87: Simplified section of model

Zoning assumptions

For creating the zones that will model the geometry of the building, DesignBuilder offers a number of possible conventions or templates. The default template of External measurements is chosen, where the surface dimensions used in thermal calculations are derived from the zone outer geometry and air volumes and floor areas from the inner geometry. It is assumed as a convention closer to the real situation of the Pal House, as the interior structure of the walls is taken as compact enough, with no contribution to the air volume of the zone. A diagram of the convention can be seen in the next:

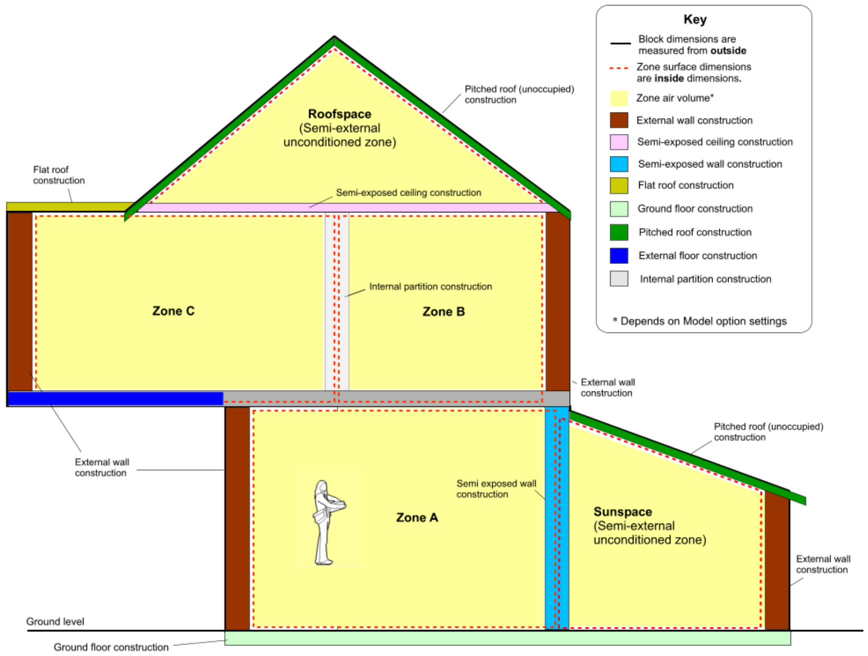


Fig. 88: External measurements template for zone configuration

As with geometry, the general suggestion for zones is to limit their number as much as possible for increasing the simulation speed and decrease convergence mistakes. The criteria for creating a new zone is that the space is having a different activity, HVAC system, different facades/walls, lightning system etc. from the existing ones. If there is no such difference, there is no need to create a new zone. In the case of the Pal house, the zones are assigned for all different rooms, as the activities and building components differ per space. Nevertheless, a single zone model could also be possible, since the air transfer between the rooms is not significantly blocked and the different activities are not usually affecting the interior climate significantly.

Other zoning assumptions include the specification of the glasshouse as a semi-exterior unconditioned space, as indeed the space in unconditioned and due to the high U-values of most of its surfaces, the difference between it and the exterior environment is not significant. Another important assumption is the connection of hall in the first floor and living room as seen in the upper left corner of the ground floor plan in Fig. 39. Although in this typology it is usual that the staircase entrance is in the front entrance hall of the house in order to avoid heat losses from the living room, due to competition restrictions it was not the case in the Pal House. This possible results to heat losses as well as some experienced draft and discomfort for the user. The connection is then modelled by creating a hole in the first floor where the staircase is. Furthermore, the triangular shape of the staircase is modelled as a parallelepiped box of half staircase length. In that way, a complex interior geometry is avoided in the model, but the correct the volume of the zone is kept. Finally, the crawl space as seen in the lower part of Fig. 40 is not simulated as a separate zone, as it is assumed to have the same conditions as the exterior (but not as the ground). Therefore the model is considered bordering with the exterior from all sides.

Material properties assumptions

In general, the simulation program offers extensive possibilities in specifying the material properties in detail. Since the building components (denoted as constructions in the program) are made from layers of different materials, the resulting U-value would require the input of all the various thermal properties (conductivity, density and thermal mass) and the separate layer thicknesses. It is apparent, that since the U-values are specified as unknown parameters and are added in the list for the calibration, it would add significantly to the model complexity, if that level of material detail is used. Furthermore, it is usual in modern building components that one layer would have the main insulating role in the construction, offering the greatest part in the U-value while the contribution of the rest is limited. It is noted however, that this is not the case for the available thermal mass calculation.

Taking also into account that EnergyPlus is not accepting U-values as direct model inputs, but rather calculates it from the various layer conductivities and thicknesses, a more simplified strategy is proposed. The construction is modeled as one material, using the total component thickness and with an “Equivalent Conductivity” value. This results from the desired U-value of the construction, divided by the total thickness. Although this conversion is not realistic from a physical point of view, it is assumed as a middle ground solution between simplicity and the required accuracy for the specific research goals. As for the thermal mass, a static value is chosen based on the typical thermal mass of timber frame panels with insulation, which comprise most of the building components of Pal House.

HVAC and use assumptions

Since the focus of the research is in the building envelope characteristics and due to restrictions in the data measuring for HVAC and user behaviour, both categories are disregarded for the model. In this way, the possible mixing of the effects of different parameters is avoided, allowing more accuracy in estimating the target parameters. Nevertheless, this suggests that the same assumptions should hold for the measured data in order for the comparison with the simulation data to be valid. Therefore, appropriate filtering will be applied to the measured data, explained in Section 4.2.

In total the following options are specified in the model:

- No active ventilation
- No active heating
- No activity

Finally, the air transfer between room-zones is considered to be minimal by having the doors are closed at all times in the model and assuming it is kept like this also in reality.

Data input process in DesignBuilder

By following the above assumptions, the model is created through the appropriate data input. The creation process included the following steps, in the order given here:

1. Add the component list
2. Add the related material list (using placeholders in unknown parameters)
3. Add the volumes - building blocks
4. Specify the zones
5. Add the glazing information
6. Format the glasshouse
7. Add external openings

It is noted that through this process, the specific model was finished in less than a working day, by having nevertheless all the data sources available already.

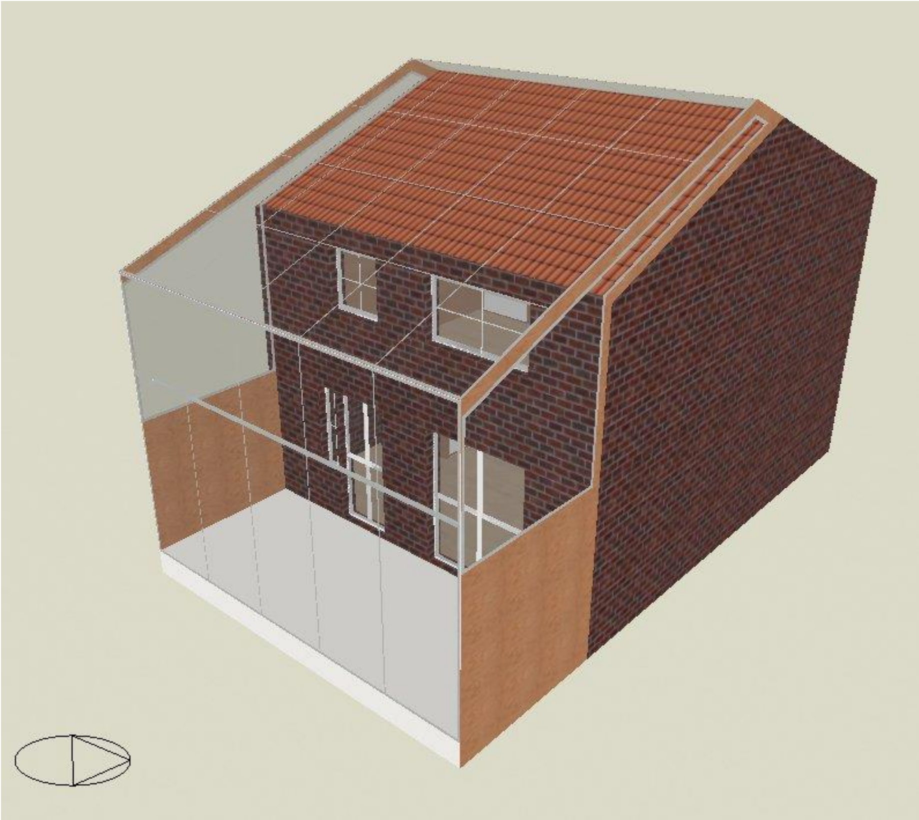


Fig. 89: Visualization of Pal house model in DesignBuilder

Weather file generation

One of the most important stages of the calibration process is to apply the same conditions to the model as in reality. In that way, the reaction of the model to these same conditions can be studied and compared. Although there is a sensor in the exterior of the house to measure the temperature and light intensity, many important parameters are missing for creating an appropriate exterior condition summary (specified as Weather File in EnergyPlus). As mentioned in Chapter 4, this information is then extracted from the site national meteorological service of the Netherlands, KNMI. The data is available both in daily and hourly base and the latter is chosen for providing the appropriate detail to the calibration. The data is extracted through API calls to the KNMI data centre and transferred automatically along with the appropriate timestamps to a csv file. From there it is converted to a Weather File, through the manual activation of the “Weather Conversion Tool” offered by EnergyPlus.

The data categories from KNMI are selected on the base of possibility of use from the Weather File (that is, if there is an appropriate mapping between them) and on relevance with the research targets and the desired accuracy.

The following parameters are extracted from KNMI and mapped to the Weather File:

- Exterior air temperature (°C)
- Exterior humidity (%)
- Dew point temperature (°C)
- Wind speed magnitude and direction (m/s and degrees)
- Atmospheric pressure (Pa)
- Precipitation (mm)
- Sky cover (octants of sky cover)
-

The first two are practically necessary for a minimal Weather File in order for EnergyPlus to solve the appropriate equations and the third for getting more meaningful results. The rest can lead to additional accuracy on the simulation, which is especially true for the wind data, in a location such the Netherlands. If no wind data is given, random data directions are used from the program leading to some inaccuracy, especially regarding the infiltration losses.

9.4 Extensive description of the Pal House

The first Solar Decathlon started as an initiative of the U.S. Department of Energy and was held at 2002 in the USA. Since then it is continued biennially in the country, but after 2010 it passed over the Atlantic where the first edition of Solar Decathlon Europe was realized in Madrid (Solar Decathlon Europe, 2014).The competition itself can be shortly described as a combination between a building fair and the Olympic Games of sustainable house.

The concept of the "Home with a skin" was first assembled in the Netherlands on the period of April-May 2014 by a consortium including the student team, faculty and industry advisors and various construction and installations sponsors. After this step, the construction team, composed by great majority by the students and led by professional technicians, deconstructed the house and managed to re-assemble it again in 11 days in the main competition period in Versailles. For the 10 following days, the house was measured by the competition committee, various testing activities were performed as well as many expert jury visits were organized. In total the Prêt-à-Loger team won 5 prizes: 1st place prize for the Communication and Social awareness and the Sustainability sub-contests, 2nd prize for the Energy Efficiency and 3rd prize for the Construction Management. Overall for all the contests, the team won the third prize with 3/1000 points difference from the first winning team (Solar Decathlon Europe, 2014).

After the end of the competition, the house was disassembled again to be transported and constructed for the last time in the premises of the Green Village in the TU Delft campus.

Technical summary and as-built plans of the Pal House

HVAC systems	
Heating and domestic hot water system	
Type	Solar Compleet Energy Panel (Heat pump coupled with thermodynamic panels)
Name	Thermboil 300 E
Capacity [W]	4000

Refrigerant	R134a
COP	3.5-4.5
Solar thermal Panels area [m2]	5.44
Storage Tank Volume [L]	300
<u>Cooling</u>	
Type	DCC-90 woningverkoeler (PCM 23)
Flow rate [m3/h]	350
Design temp [C]	23
Cooling Capacity [Wh]	5530
COP	-
<u>Heat recovery Unit</u>	
Type	HRU ECO-fan 3
Capacity [m3/h]	max 325
Efficiency	96%
Power [W]	0-150
Electrical Energy Production	
PV Modules Type	DMEGC mono c-Si glass-glass customized
PvV panels area [m2]	43.61
Installed PV power [kWp]	4.875
Estimated energy production [kWh/year]	3811
Energy consumption	
Estimated energy consumption [kWh/year]	2354
Estimated energy consumption per conditioned area [kWh/year per m2]	27.69
Cooling	3.6%
Ventilation	4.25%
Domestic Hot Water	17.03%
Lighting	13%
Appliances and Devices	62%
Energy balance	
Estimated energy balance [kWh/year]	1457

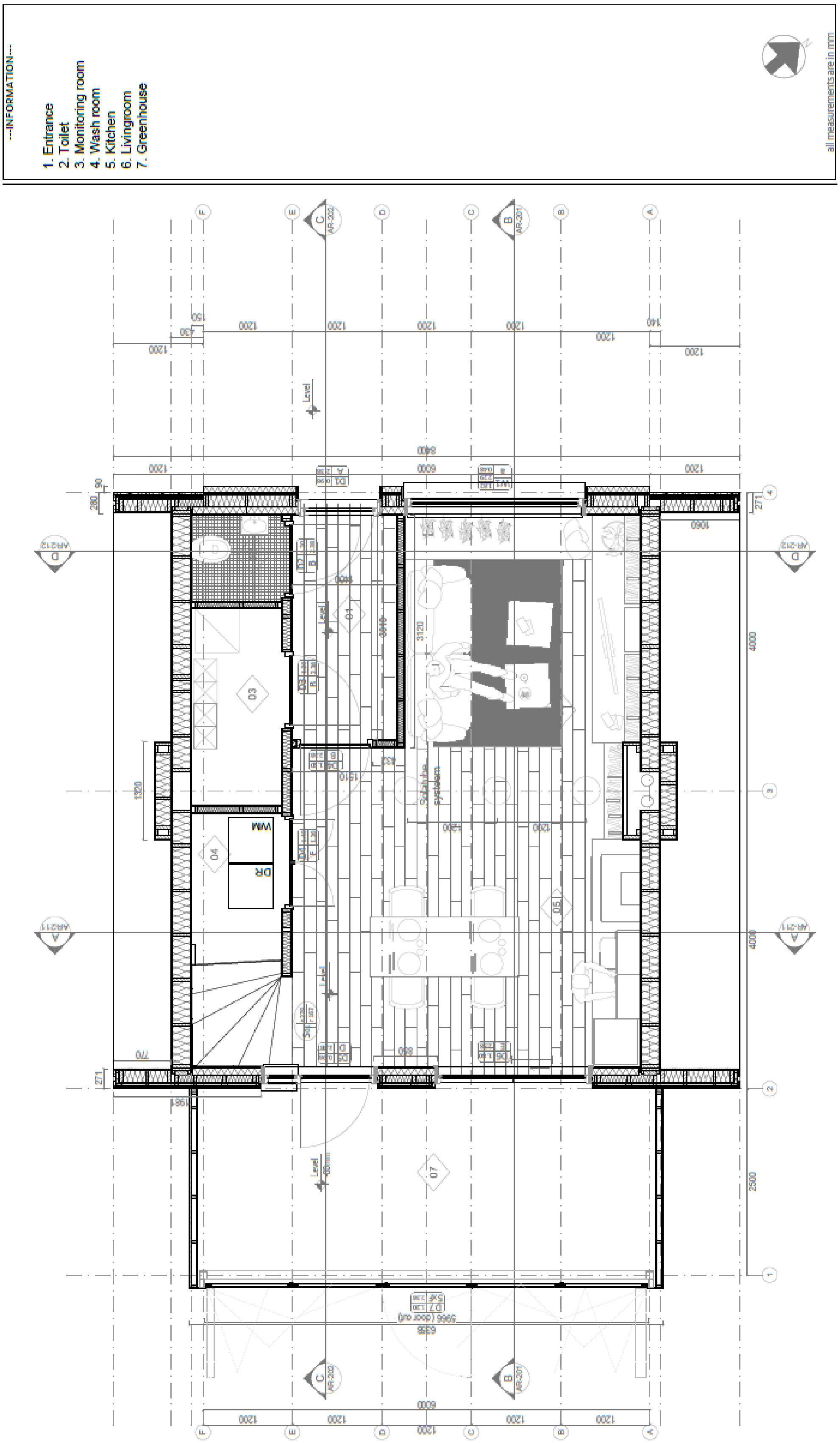


Fig. 90: Ground floor plan of prototype house (Pret-a-loger, 2014)

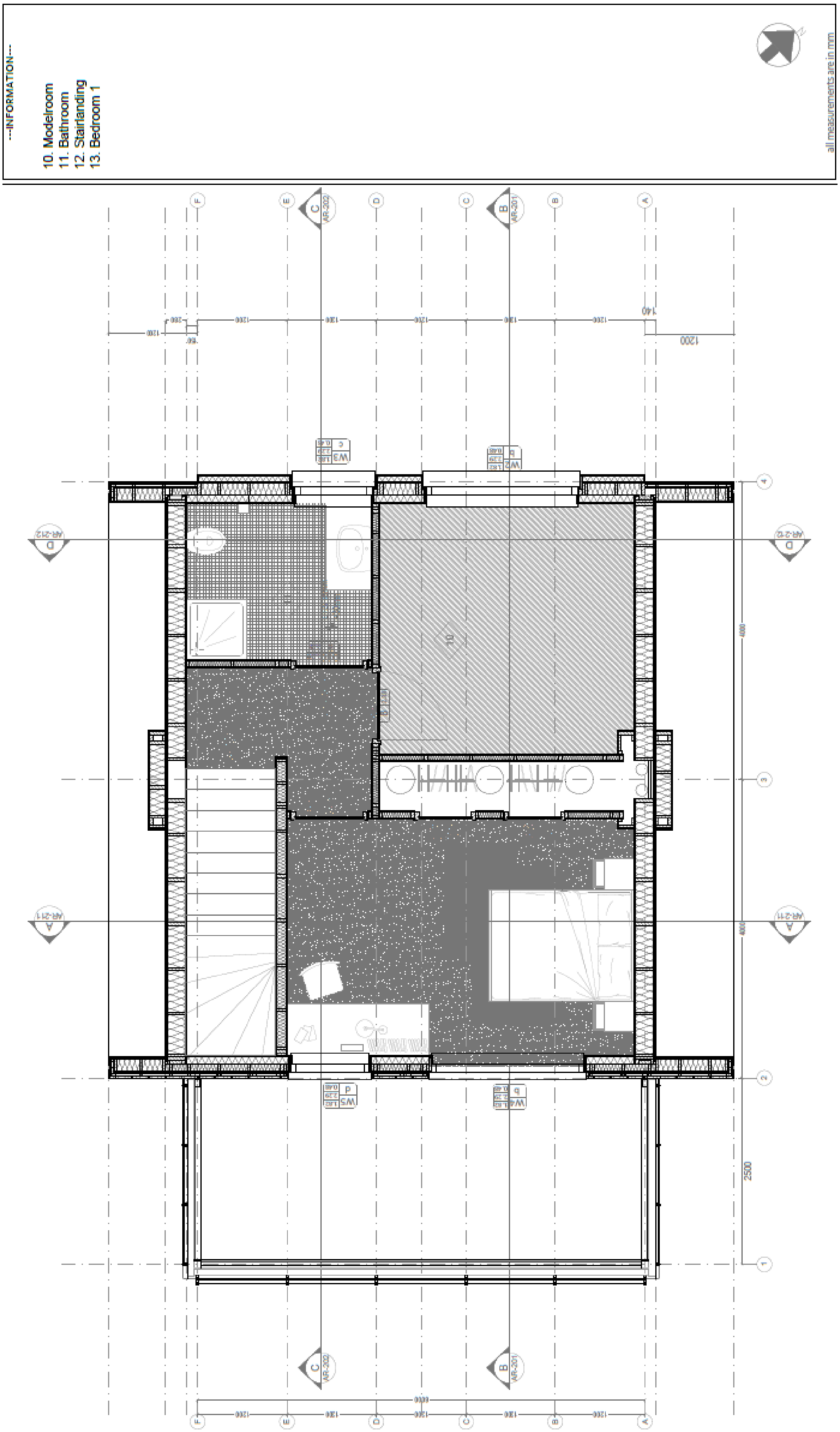


Fig. 91: 1st floor plan of prototype house (Pret-a-loger, 2014)

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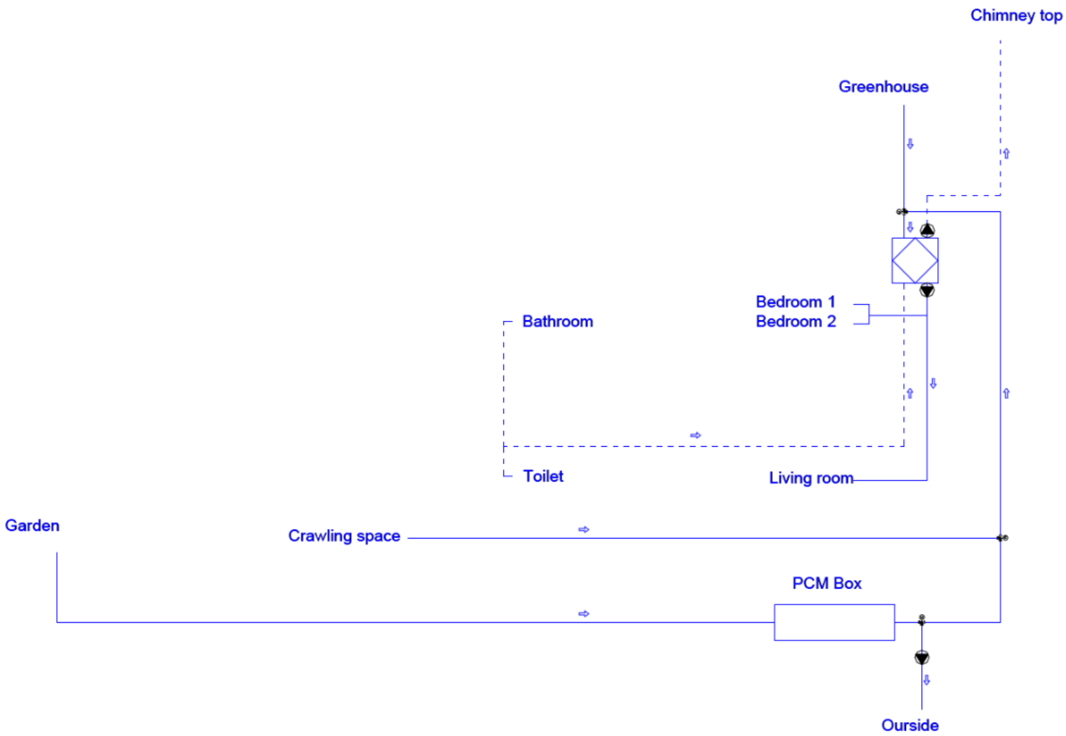


Fig. 92: Ventilation scheme (Pret-a-loger, 2014)

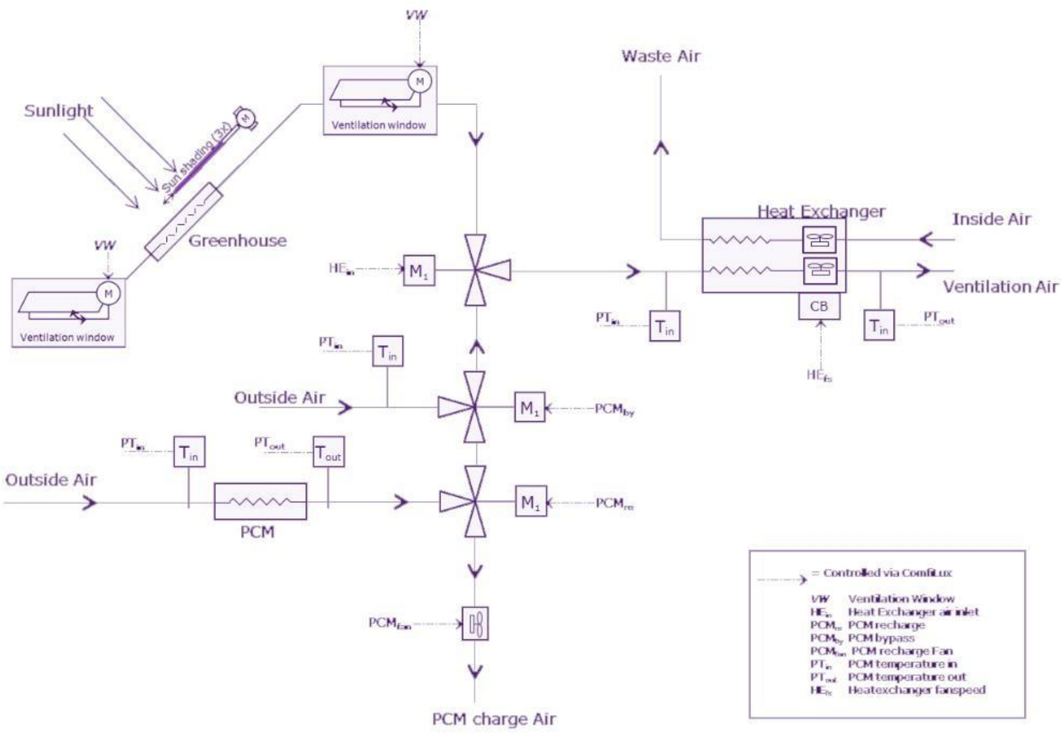


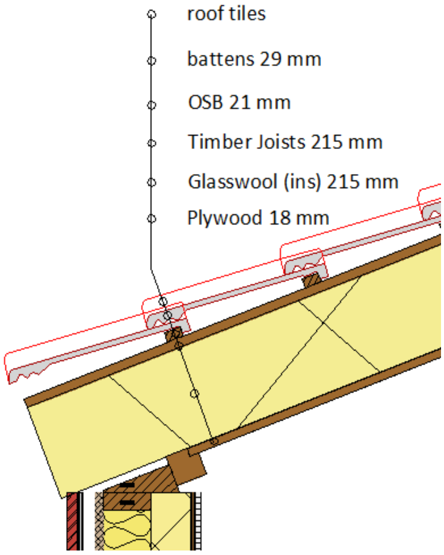
Fig. 93: Monitoring scheme for ventilation, window and sun-shading control (Pret-a-loger, 2014)

Building element composition

In the following the composition of the building elements of the PaL House can be found, derived from the as-built documentation.

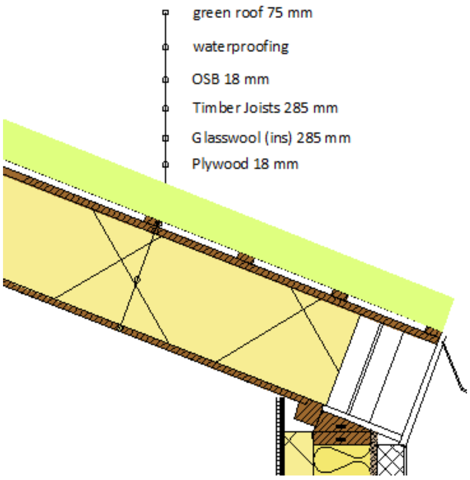
South roof

Datasheet	
U_{value} (W/m^2*K)	0.1376
R (1/U)	7.27
Total thickness (m)	0.274
Equivalent conductivity (W/m*K)	**0.0377**



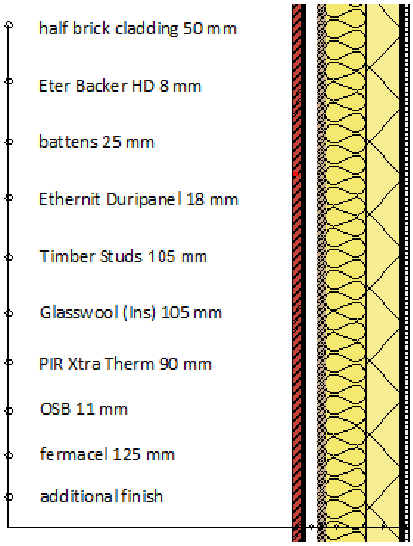
North roof

Datasheet	
U_{value} (W/m^2*K)	0.1051
R (1/U)	9.51
Total thickness (m)	0.321
Equivalent conductivity (W/m*K)	**0.0337**



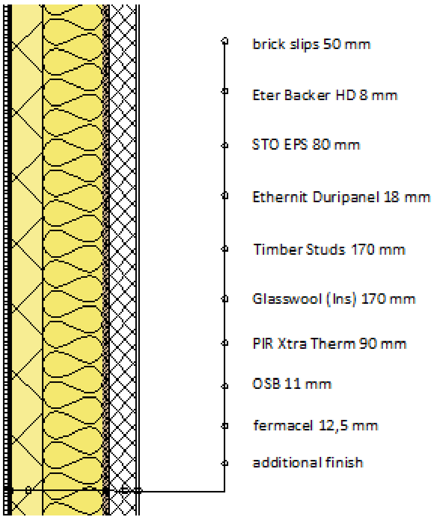
South wall

Datasheet	
U_{value} (W/m²*K)	0.1286
R (1/U)	7.78
Total thickness (m)	0.32
Equivalent conductivity (W/m*K)	**0.0412**



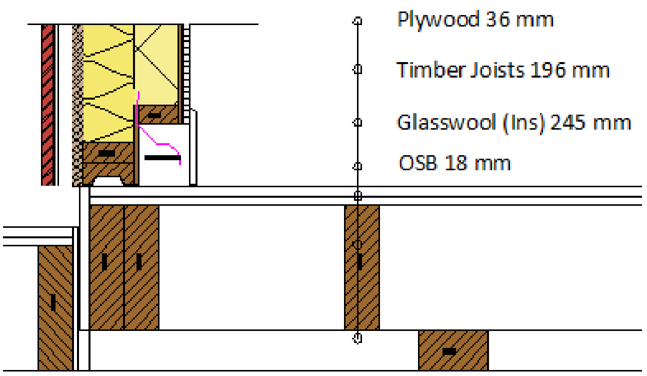
North wall

Datasheet	
U_{value} (W/m²*K)	0.0823
R (1/U)	12.15
Total thickness (m)	0.489
Equivalent conductivity (W/m*K)	**0.0402**



Ground floor structure

Datasheet	
U_{value} (W/m^2*K)	0.1238
R (1/U)	8.08
Total thickness (m)	0.299
Equivalent conductivity (W/m*K)	**0.0370**



Side walls (East-West side)

Side walls	
U_{value} (W/m^2*K)	0.149
R (1/U)	6.70
Total thickness (m)	0.28
Equivalent conductivity (W/m*K)	**0.0418**

Interior walls/110mm

Interior walls/110mm	
U_{value} (W/m^2*K)	1.136
R (1/U)	0.88
Total thickness (m)	0.11
Equivalent conductivity (W/m*K)	**0.1250**

Interior walls/150mm

Interior walls/150mm	
U_{value} (W/m^2*K)	1.136
R (1/U)	0.88
Total thickness (m)	0.15
Equivalent conductivity (W/m*K)	**0.1705**

First floor structure

First floor structure	
U_{value} (W/m^2*K)	1.136
R (1/U)	0.88
Total thickness (m)	0.218
Equivalent conductivity (W/m*K)	**0.2477**

Modifications between the existing and the refurbishment prototype

The prototype house is in principle a replica of an existing row-house transformed to a zero-energy dwelling by an integrated renovation system. Since the target of the prototype was the participation to the Solar Decathlon, many design modifications occurred due to the requirements and restrictions of the competition.

Fig. 94: Design process transition from the existing to renovated situation and the competition pavilion

Specifically, the most important of them are changing the floor number from 3 to 2, scaling down the size of the house to fit the requested solar envelope and represent the original brick walls with timber frame panes due to the transportation and assembly limitations of the competitions. This results in a significant reduction of the thermal mass of the walls which is also reducing the time delay of the system for anticipating the external conditions and the difference between radiative and mean air temperature. Nevertheless, the design process of the prototype house, followed the refurbishment process as would it be executed for the original house.

Fig. 95: Existing Honselersdijk house (left) and refurbished prototype (right)

Climate system – installations

The following system description is summarized from the project manual of Pret-a-loger (2014). The design of the climate and installation system is based in making the existing house effectively adaptive for the different seasons of the year. This is succeed by taking into account the local climate, the characteristics of the existing structure, the criterion of minimum intrusion of refurbishment process and the desired functionality.

This results to an integrated solution that not only focuses in creating a zero energy house but also an elevated user experience all-year round.

As expected for a north-western European country, the focus of the system is on anticipating the low winter temperatures and minimizing the heating requirements. The main solution introduced for this is the southern glasshouse, functioning as a thermal buffer, effectively reducing the energy demand by 34%. Combined with double-E glazing windows, thick building envelope insulation and improved airtightness, it results to a total energy reduction of 79% and a yearly consumption of 1780 kWh. The heat for the heating and hot tap water is produced by a solar thermal system. Two thermodynamic panels extract the heat from the glasshouse and transport it towards a heat pump which heat a 300 liter water tank to 55 °C. The system has enough power to warm the 6 already existing radiators in the house. The radiators can then be heated with a lower temperature since the energy demand is reduced (and only need 1900W instead of 8500W). In winter the mechanical ventilation system brings the temperature to the preferred level, largely supported by using pre-heated air from the glasshouse and a Heat Recovery Unit of 96% efficiency. The balanced ventilation is CO2 driven and controlled by the home automation system.

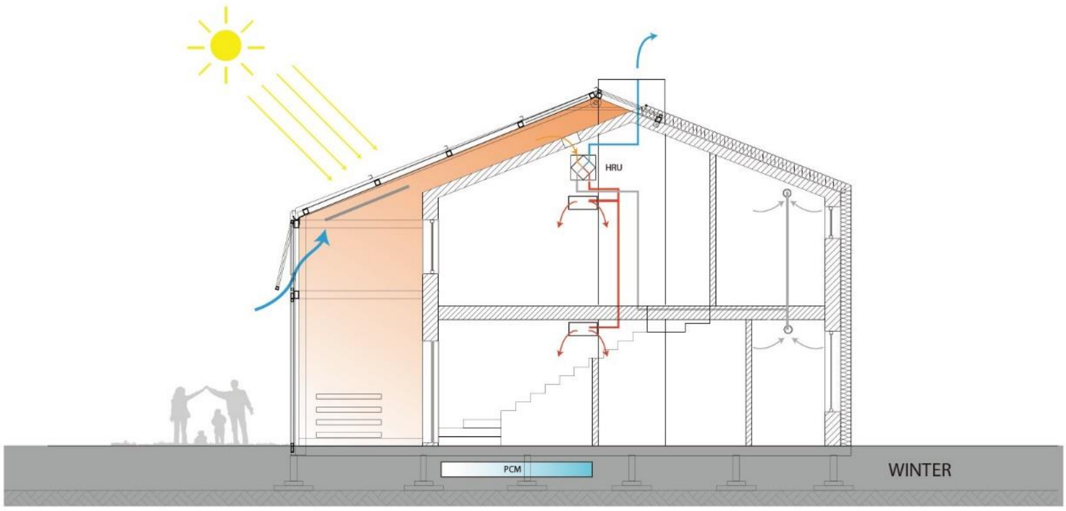


Fig. 96: Climate system functions in the winter (Pret-a-loger, 2014)

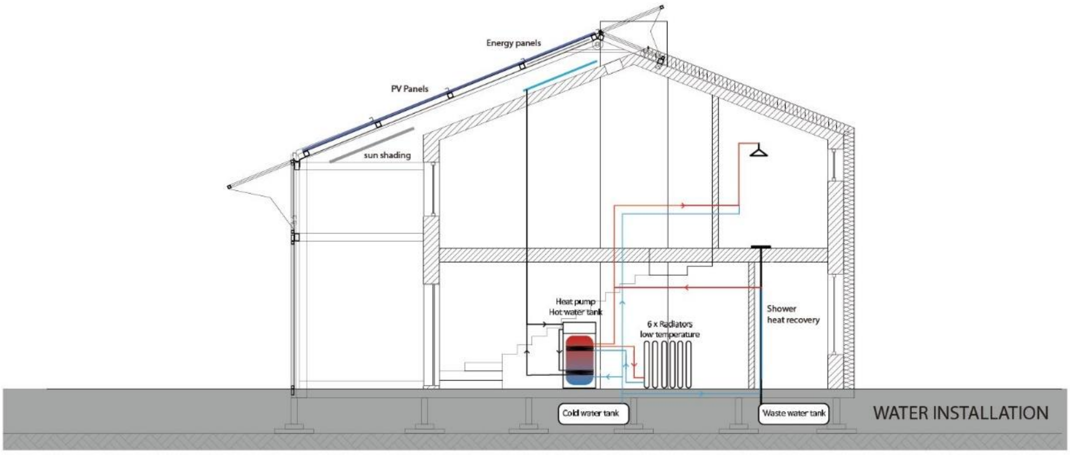


Fig. 97: Diagram of installations in the house (Pret-a-loger, 2014)

In the mild and wet seasons of autumn and spring, the glasshouse is gathering heat from the increased sunshine that can be then used the passive heating of the house, by opening the doors and windows towards it. The monitoring of the temperatures and their availability by the automation system to the user are playing the significant role of a climate advisor, pinpointing the correct moment for it. The user can also control the sun-shading and the glasshouse windows through the manual mode of the system, to modify the living climate per preference. In automatic mode, the system can control the installations and movable parts of the house in order to achieve the target temperatures. Furthermore, Solartubes are installed to bring more natural light to the centre of the deep living room, thus improving visual conditions and reducing light use in the day hours. A water collecting system is also installed for gathering rain water for use in flushing the toilets and watering the plants saving almost 29500 liters water every year, while a green roof is created in the north, keeping the water and improving the ecology.

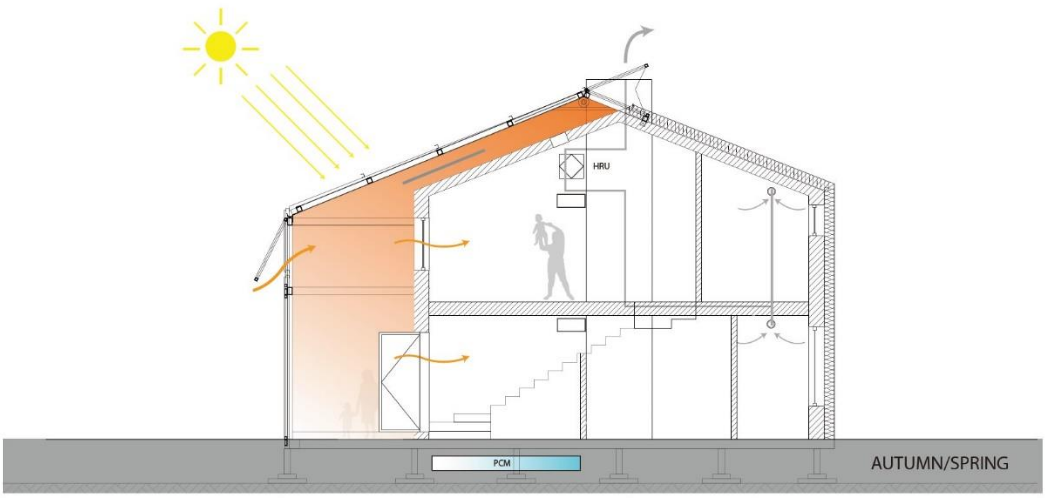


Fig. 98: Climate system functions in autumn/spring (Pret-a-loger, 2014)

In summer the system's function is to retain comfortable temperatures in the house while producing the bulk of energy to render it zero-energy on a yearly basis. The northern side protects the house with the extra isolation layer and the green roof while the glasshouse in the south can open up completely to create draft and further block the sun intrusion through sun-shading. By opening up a space connection is also created, extending effectively the house to the garden. In parallel, integrated photovoltaic panels on the glasshouse of total 4.9 Wp power, produce over 3700 kWh yearly. The energy use can be further optimized, by providing the user with information from the energy production and consumption monitoring, in order to use the surplus of the energy balance in the day hours to power the most demanding appliances. Finally for avoiding extreme overheating a ventilation system with phase-changing materials is used in order to cool the air before it enters the house.

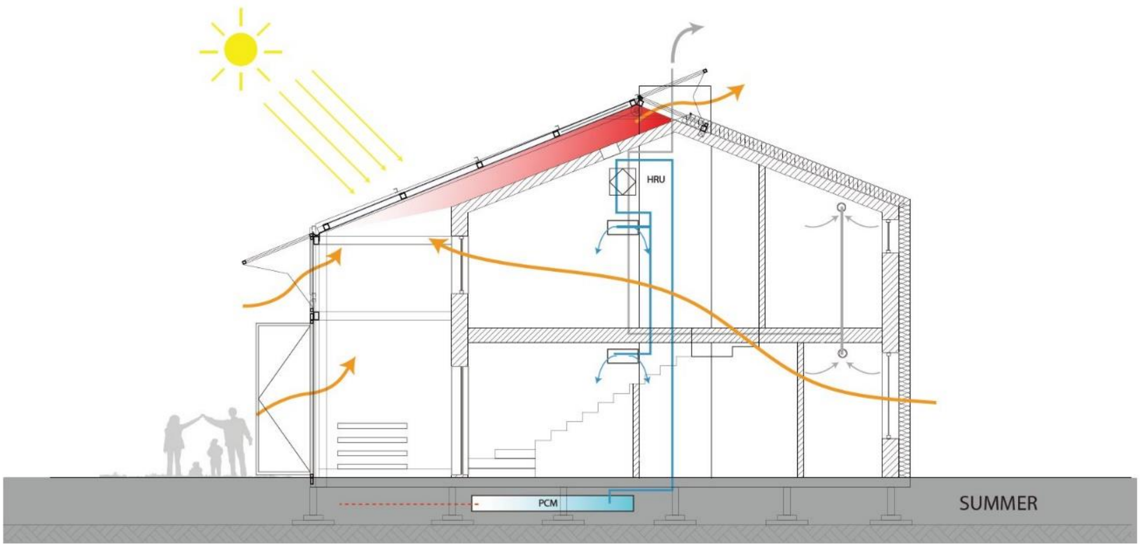


Fig. 99: Climate system function in the summer (Pret-a-loger, 2014)

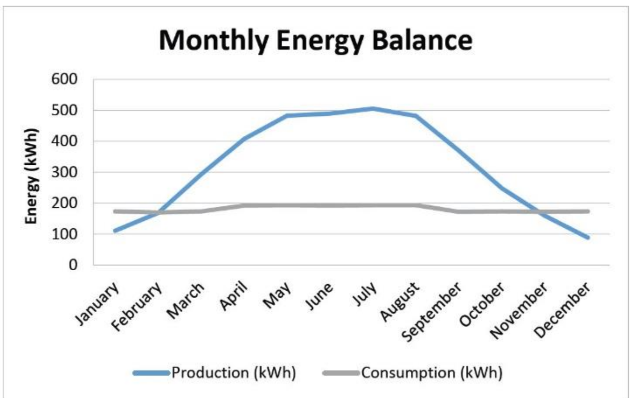


Fig. 100: Monthly energy balance estimation for the prototype house (Pret-a-loger, 2014)

A detailed technical summary, the floor plans of the ground, 1st floor of the prototype house and technical specification plans are presented in Section 9.4.

Initial measured data observations

As shown previously in the domotica description, the extensive monitoring and control of the house result to a great number of time-series, currently a little less than 200. As the data of the time-series is stored in the database in large text-like files of csv format (comma-separated-values), it is usual practice that a plotting method is used in order to even get an initial grip of this data. Other points where a plotting method would be useful are the following:

- Comparison between different time-series (e.g. exterior and interior temperature)
- Parallel plotting of time-series in order to pinpoint possible effects or interest points (e.g. plotting the motion sensor data along with the temperature in a room)
- Discover visually inconsistencies or outliers in the measured data.

Therefore a plotting component is developed. The main input of this component is a dataset in a pandas.DataFrame format, which for simplicity can be thought similar to an excel file with the first column being the timestamps and the rest of the columns the datapoints of various time-series. The main output is a diagram that can be interactive (e.g. show a point's 'coordinates' - <timestamp>-<value> pairs) and can be also saved in image format for use in the documentation. The component includes also various sub-methods for arranging the illustration format, show statistical indices, legends etc.

This component is then used to produce the following diagrams, to show some visual examples of the time-series and make some initial observations on the monitored data

Versailles dataset

PV production vs house consumption – power – 2 and 8 July

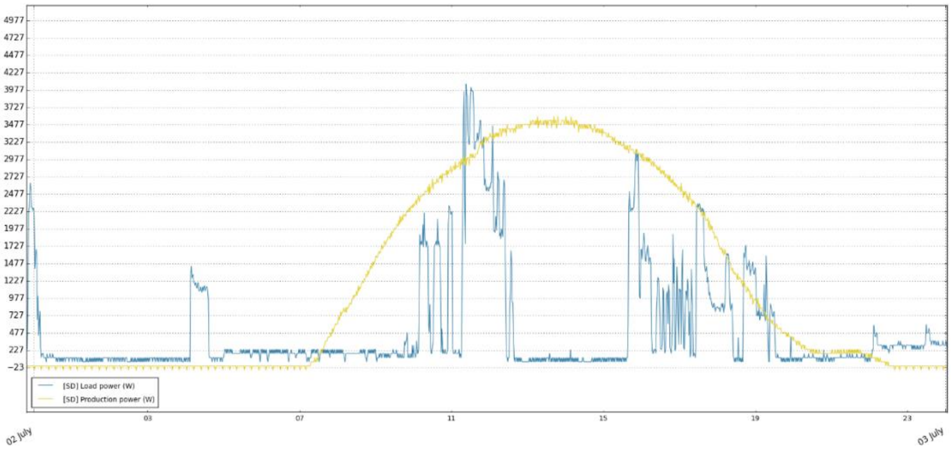


Fig. 101: PV production vs consumption power in a sunny day (Versailles dataset)

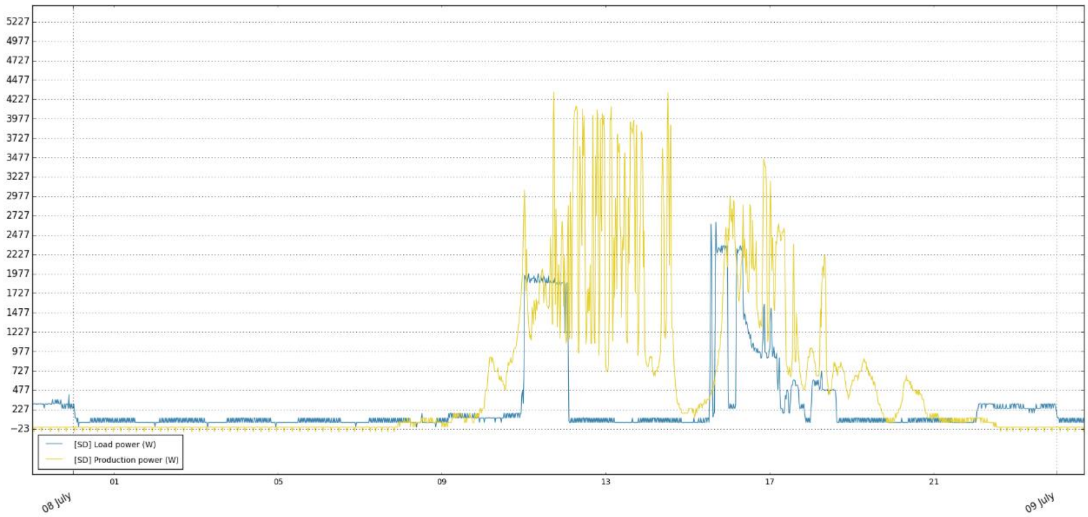


Fig. 102: PV production vs consumption power in a cloudy day (Versailles dataset)

The production power forms an almost perfect bell-shaped curve in a completely sunny day (upper) and was enough to cover most of the consumption power needs of the house. Some uncovered peaks are still present for limited time. In a partly cloudy day (lower), the production curve is dissolved in many peaks due to the partly covered direct radiation and a smaller bell-shaped curve from the diffuse radiation. This is covering some of the consumption needs of the house but in a less effective way than before.

PV production vs house consumption – energy – 30 June – 11 July (competition duration)

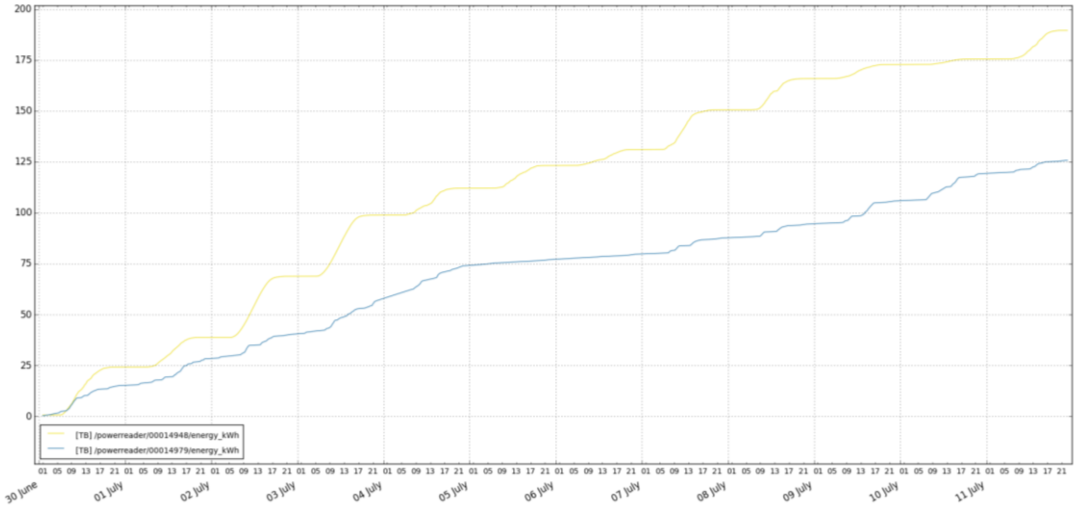


Fig. 103: PV production vs consumption energy (Versailles dataset)

The final production was almost 190 kWh versus the 125 kWh consumed in the house, rendering the house as energy positive. During the whole period of the competition the energy production curve (yellow) was significantly higher than the total energy consumption (blue) as shown above.

Exterior vs living room vs target interior temperature – 07 July

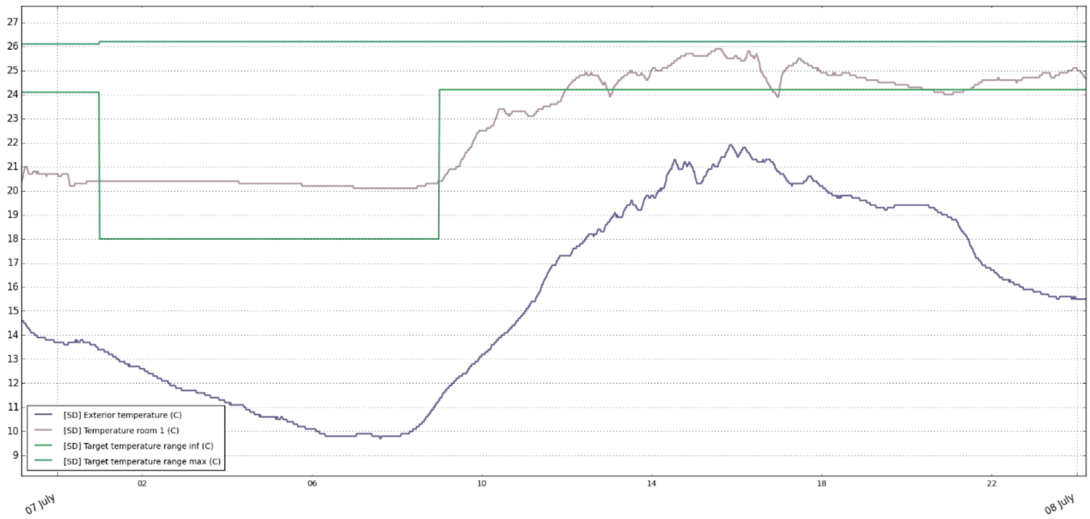


Fig. 104: Exterior vs living room vs target interior temperatures (Versailles dataset)

The temperature in the living room (purple) followed approximately the variations of the exterior temperatures (blue) with less intensity nevertheless, possibly due to the insulation of the house. No significant time-lag effect is observed, due to the small thermal mass of the construction materials of the house. The interior temperature is staying almost inside the target temperature limits (green), with a small delay in the beginning.

Delft dataset

<u>External vs living room vs glasshouse temperature – 13 – 22 October</u>

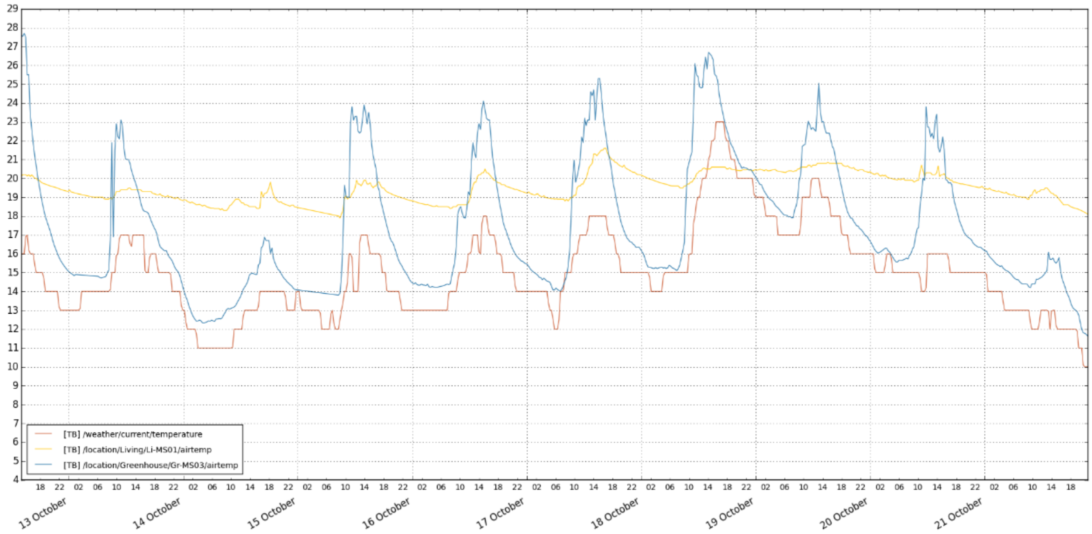


Fig. 105: External vs living room vs glasshouse temperature between October 13th and 22nd (Delft dataset)

The daily variation of the living room temperature (yellow) is significantly smaller than the exterior temperature (red), in comparison with the glasshouse (blue) that is even augmented by the captured solar radiation.

External vs living room vs glasshouse temperature – 18 October

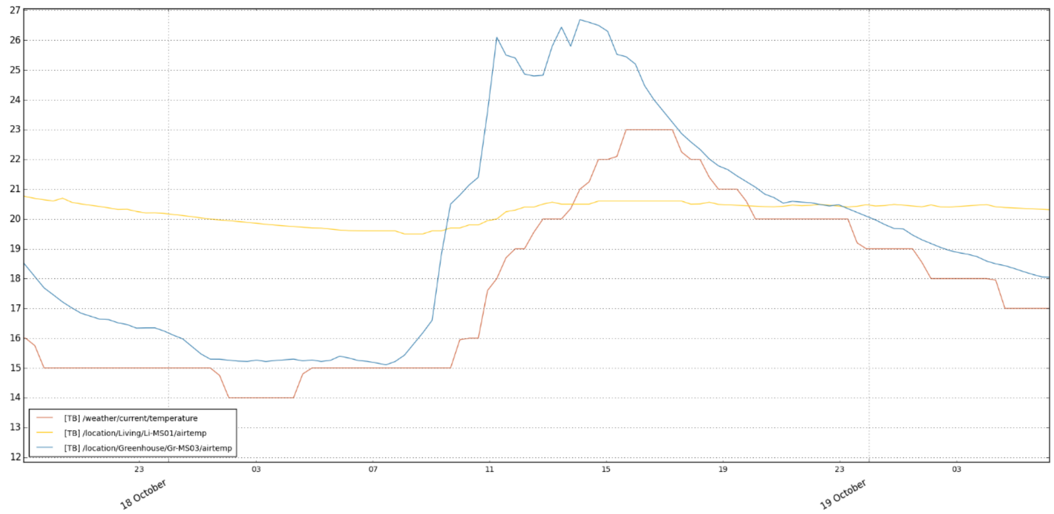


Fig. 106: External vs living room vs glasshouse temperature on October 18th (Delft dataset)

The living room temperature stays almost constant between 20-21 degrees while the door leading to the glasshouse and the elevated temperatures of about 26 degrees is closed.

External vs living room vs glasshouse temperature – 17 October

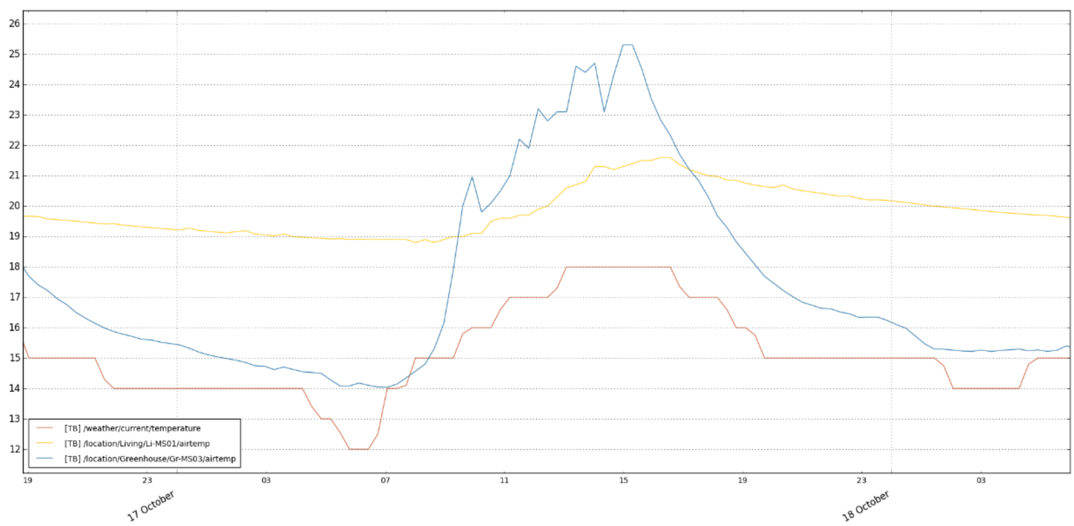


Fig. 107: External vs living room vs glasshouse temperature on October 17th (Delft dataset)

With the glasshouse door open, the living room temperature is rising more than 2 degrees, while the exterior temperature stays lower.

External vs living room vs glasshouse temperature – 13-17 October

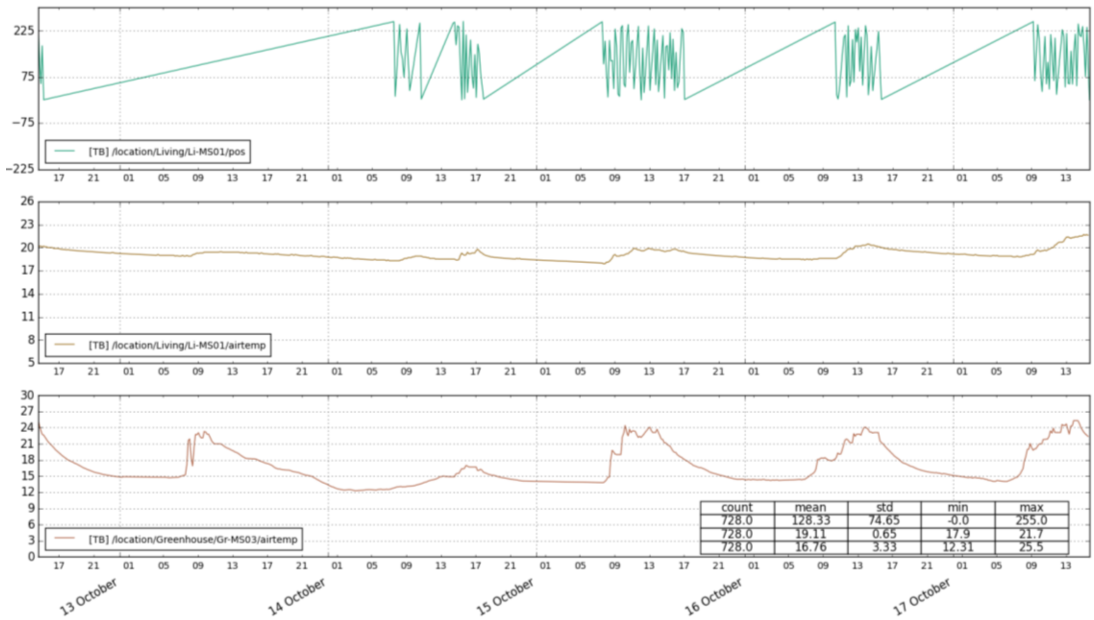


Fig. 108: Living room vs glasshouse temperature vs occupancy between October 13th and 22nd (Delft dataset)

The observation above can be also seen in parallel with the motion sensor (green) in the house, where the living room temperature (yellow) follows the temperature rise in the glasshouse (red) when somebody is in the house and possibly opens the door.

9.5 Sensitivity analysis – Energy diagrams

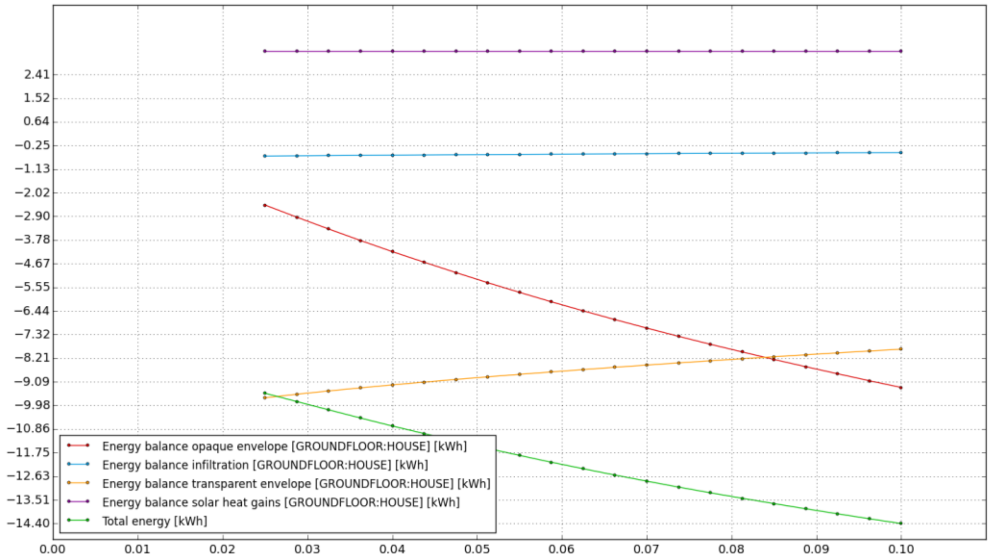


Fig. 109 Heat loss diagram for fluctuating opaque envelope equivalent conductivity (kWh)

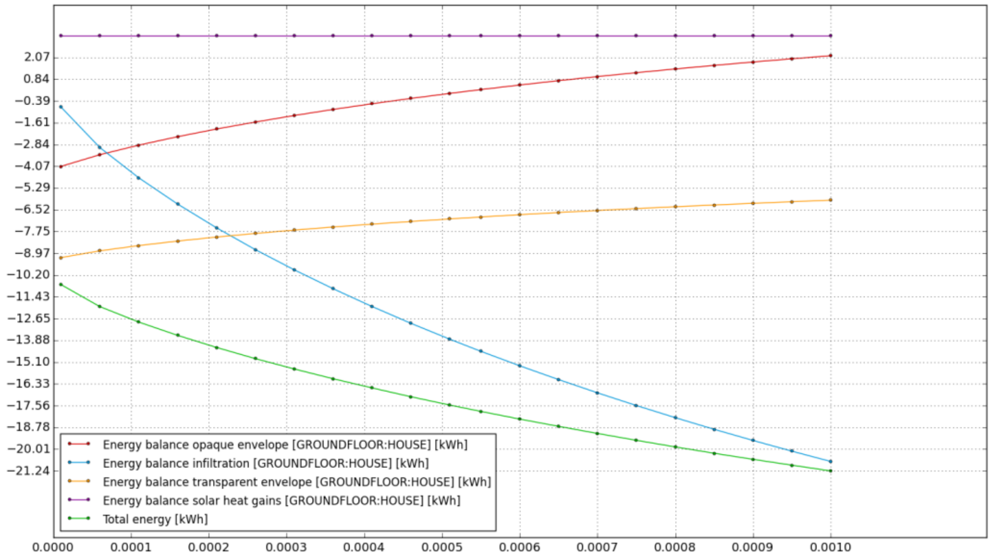


Fig. 110: Heat loss diagram for fluctuating infiltration flow coef. (kWh)

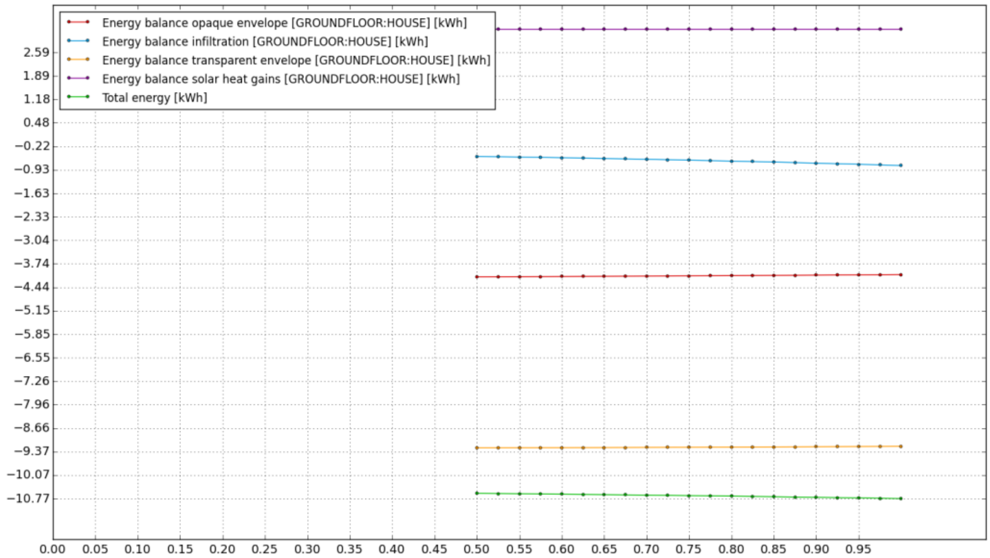


Fig. 111 Heat loss diagram for fluctuating infiltration flow exp (kWh)

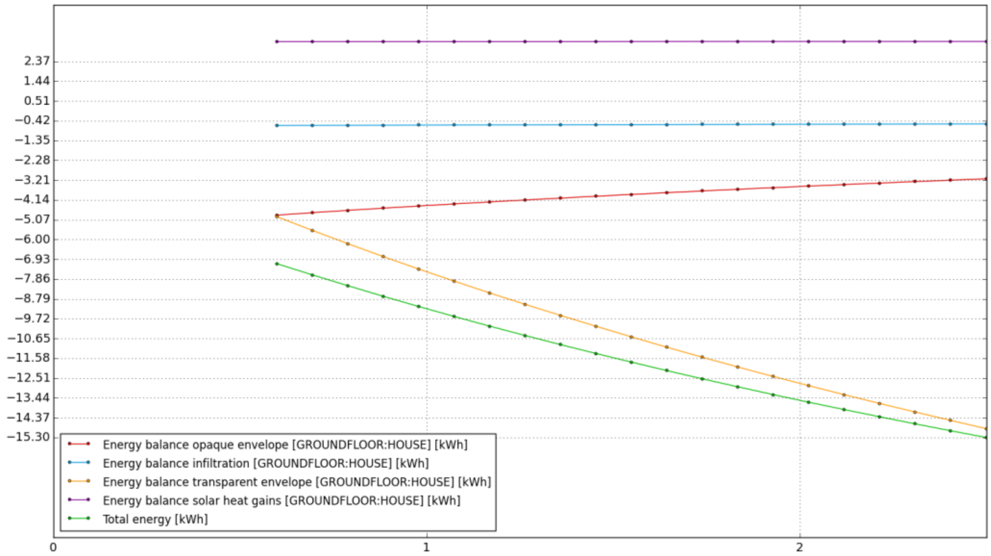


Fig. 112 Heat loss diagram for fluctuating transparent envelope U-value (kWh)

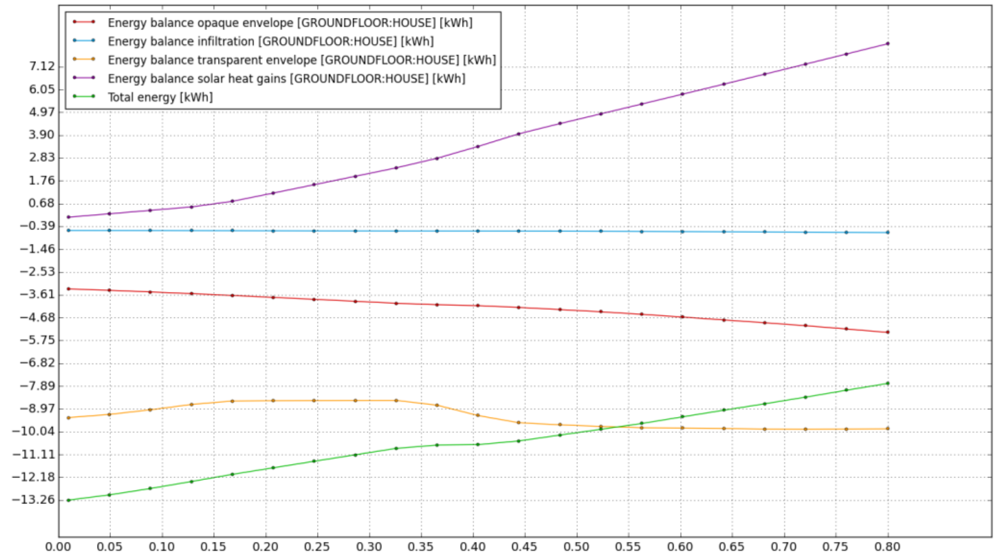


Fig. 113 Heat loss diagram for fluctuating solar gain (kWh)

9.6 Validation - Analytic results

Multi-parameter model comparison

As mentioned in the problem statement in Chapter 2, the multi-zone, multi-parameter model is not used for calibration. The reason is that the way that a BPS simulation captures the effects in heat losses from varying e.g. the conductivity of various walls in a zone, does not provide accuracy for each separate element, but rather for all the building elements as a whole. In order to demonstrate this effect, a calibration with a multi-parameter model is attempted. The results can be seen below in the convergence diagram for all the different zones and the calibrated parameters for the different building elements and zone infiltrations. The results of only two calibrations are shown here for comparison, as the other runs that performed show similar results.

From the convergence diagram it can be seen that there is significant convergence for all the zones of the model. Specifically, the error goes from around 15% for most zones to less than 5%. Nevertheless, as observed from the parameter comparison table, the parameters are not converging to their target values as it was the case in the single-zone simulation. Specifically, the conductivities of the different building elements are fluctuating around the target value of 0.04 W/m2K, without a possible correlation with their positioning in the house. Also, the results between the two runs with a similar convergence show that there is no apparent pattern between the parameter and its calibration value, i.e. that a parameter is not calibrated to the same values in both runs.

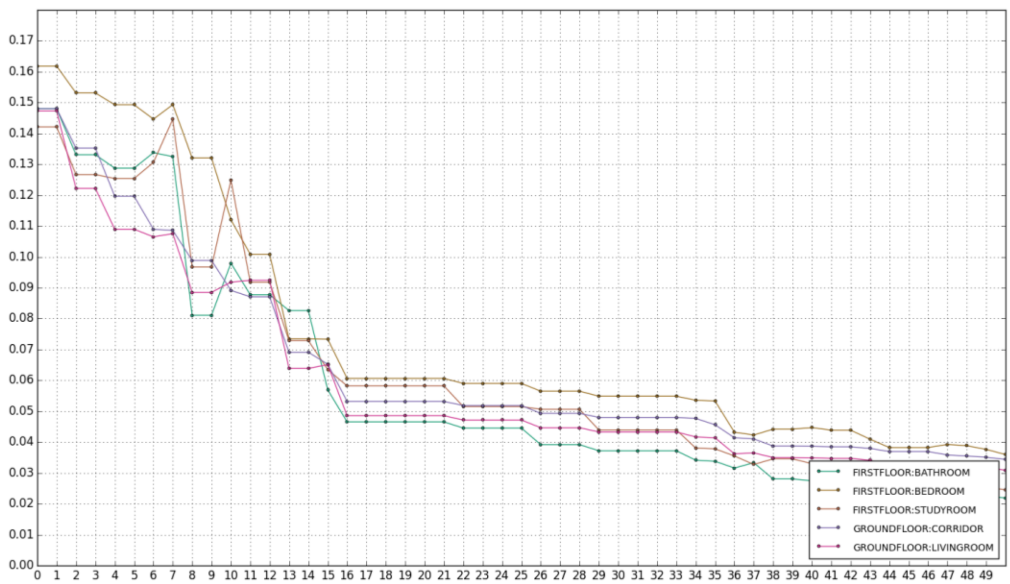


Fig. 114: Algorithm convergence diagram for a 5-zone model

	Target	Calibration results (2 runs, same config)	
PalCFg	0.04	0.030	0.030
PalCRn	0.04	0.031	0.040
PalCRs	0.04	0.084	0.090
PalCWe0e	0.04	0.030	0.034
PalCWe0n	0.04	0.058	0.046
PalCWe0s	0.04	0.030	0.048
PalCWe0w	0.04	0.082	0.030
PalCWe1e	0.04	0.062	0.031
PalCWe1n	0.04	0.030	0.036
PalCWe1s	0.04	0.073	0.105
PalCWe1w	0.04	0.075	0.059

Table 19: Multi parameter model comparison

Time statistics

In the following table an indication of the time needed to run the calibration process is given. The average time per analysis is 2.4 sec, noted as "mixed" to indicate that this includes the EnergyPlus analysis calculation as well as the various read/write processes that are part of it.

2.4	**sec/per analysis (mixed)**			
Pop	ngen	mixed runs	minutes	hours
10	100	1000	41.67	0.7
20	100	2000	83.34	1.4
30	100	3000	125.01	2.1
40	100	4000	166.68	2.8
50	100	5000	208.35	3.5
60	100	6000	250.02	4.2
70	100	7000	291.69	4.9
80	100	8000	333.36	5.6
90	100	9000	375.03	6.3
100	100	10000	416.7	6.9

Table 20: Time statistics

The most important relevant specifications of the used hardware are:

- **CPU**: Inter Core 2 i7–4700MQ @ 2.40GHz
- **RAM**: 8.00 GB DDR3
- **Storage**: SSD drive
- **O/S:** Windows 8.1 (64bit

9.7 Initial research – noisy data

Single-zone model with polynomial factors

To rectify the possible oversimplification by a lumped mass model, a single-zone calibration model with polynomial factors can be examined. These factors are incorporated to the curve deriving from the simulation results in order to provide the maximum possible fitting with the measured data. Although these factors don't have an apparent physical meaning, it is assumed that they can make up for the accumulated error from the physical phenomena that were not simulated in the model. In that way, a mix of methods is used to provide a prognostic model for a specific house. It is noted that the accuracy of these factors can be possibly further increased by enlarging the measured data sample.

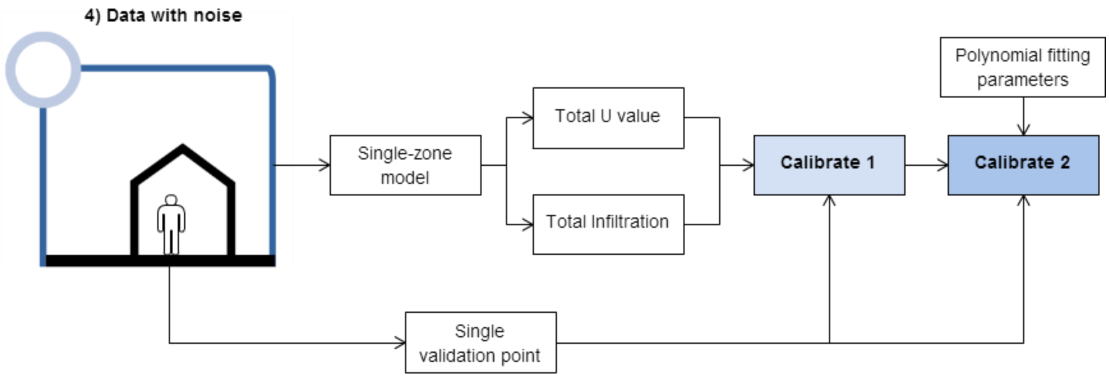


Fig. 115: Process for data with noise

9.8 Computational components developed

As one of the two main targets of the thesis, the automation of a process to find and analyse the difference between the measured and simulated data is presented in this section. This process includes the creation of strategies for tackling limitations (such as the automatic matching of the initial conditions of the simulation period to the respective measuring data) as well as the description of custom computational components developed for achieving a workflow. These development products were the result of the analysis of the measured data, the simulation opportunities and the targets set from the thesis proposal. In other words, they form possible solutions for the requirements set for achieving the goal of this thesis, with the data and the tools that were available at the time of writing it. Finally, the components provide an adaptable framework in which various methods can be built in and provide further data analysis and functionality.

In the following the base computation components are listed. The form of these components resulted iteratively through the requirements of the thesis, starting from a stand-alone script to perform a specific function and ending as class objects that were further inherited and expanded depending on the use.

- Data fetcher
- IDF manipulation
- Energy plus tools
- Warmup component
- Base analysis
- Data filtering

9.9 Proposals for scaling the method

Finally some proposals on the scaling of the method to include more validation points (e.g. energy meters) can be found in the following diagrams. There they are presented in more details and in the parallel layers of the user story of the designer-engineer, the necessary features and thus the development effort needed.

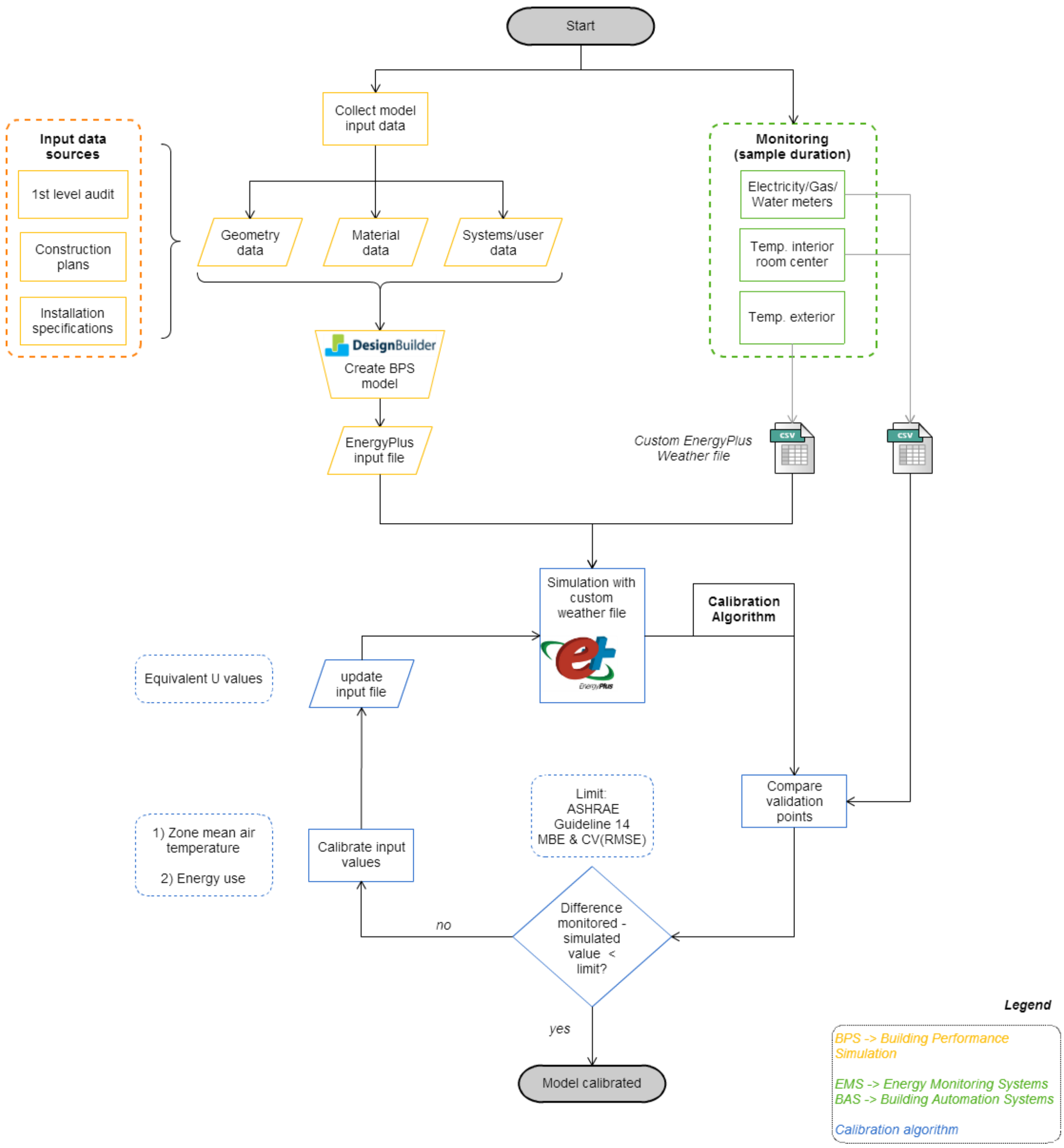


Fig. 116: Detailed calibration methodology

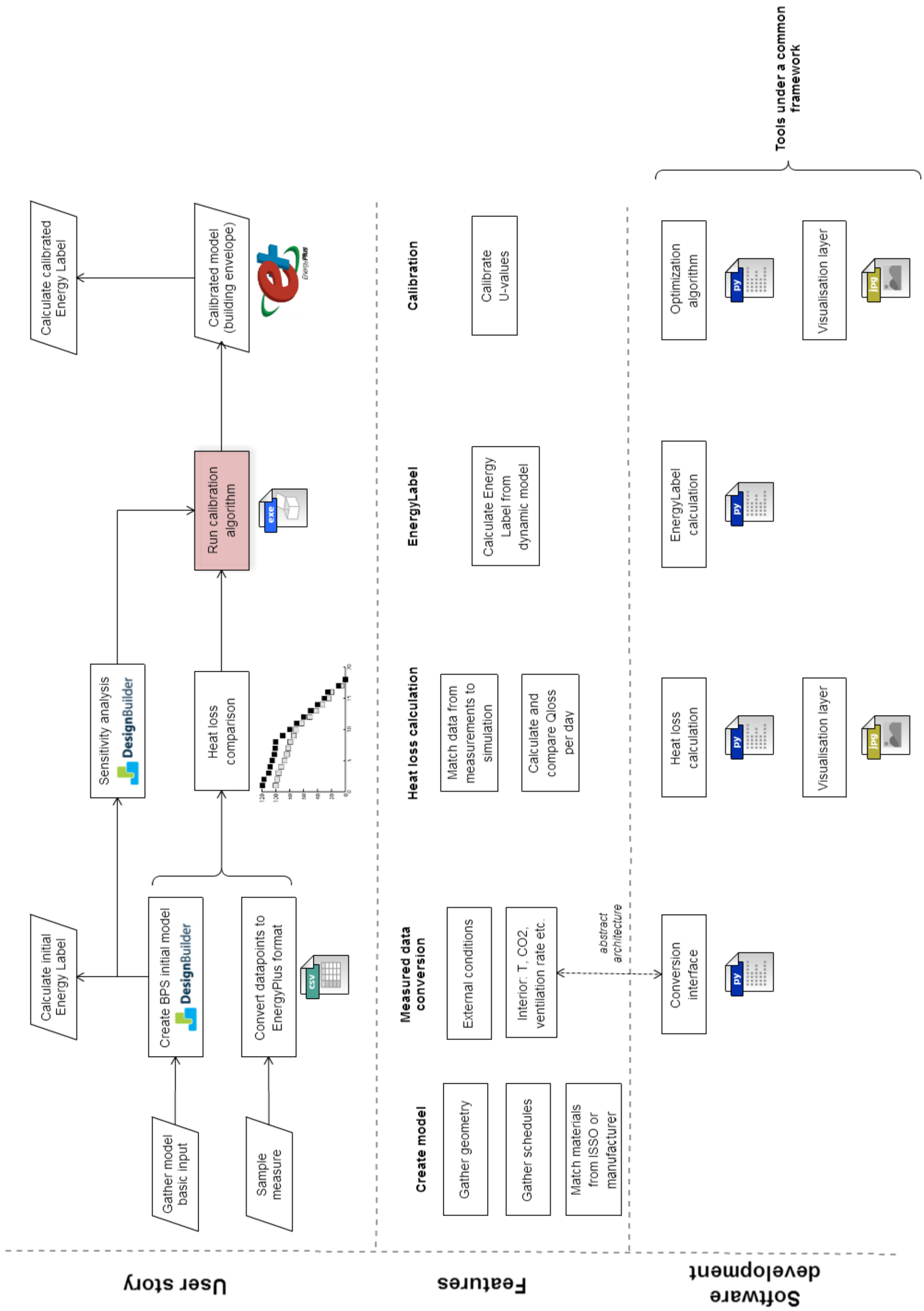


Fig. 117: Detailed development methodology

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