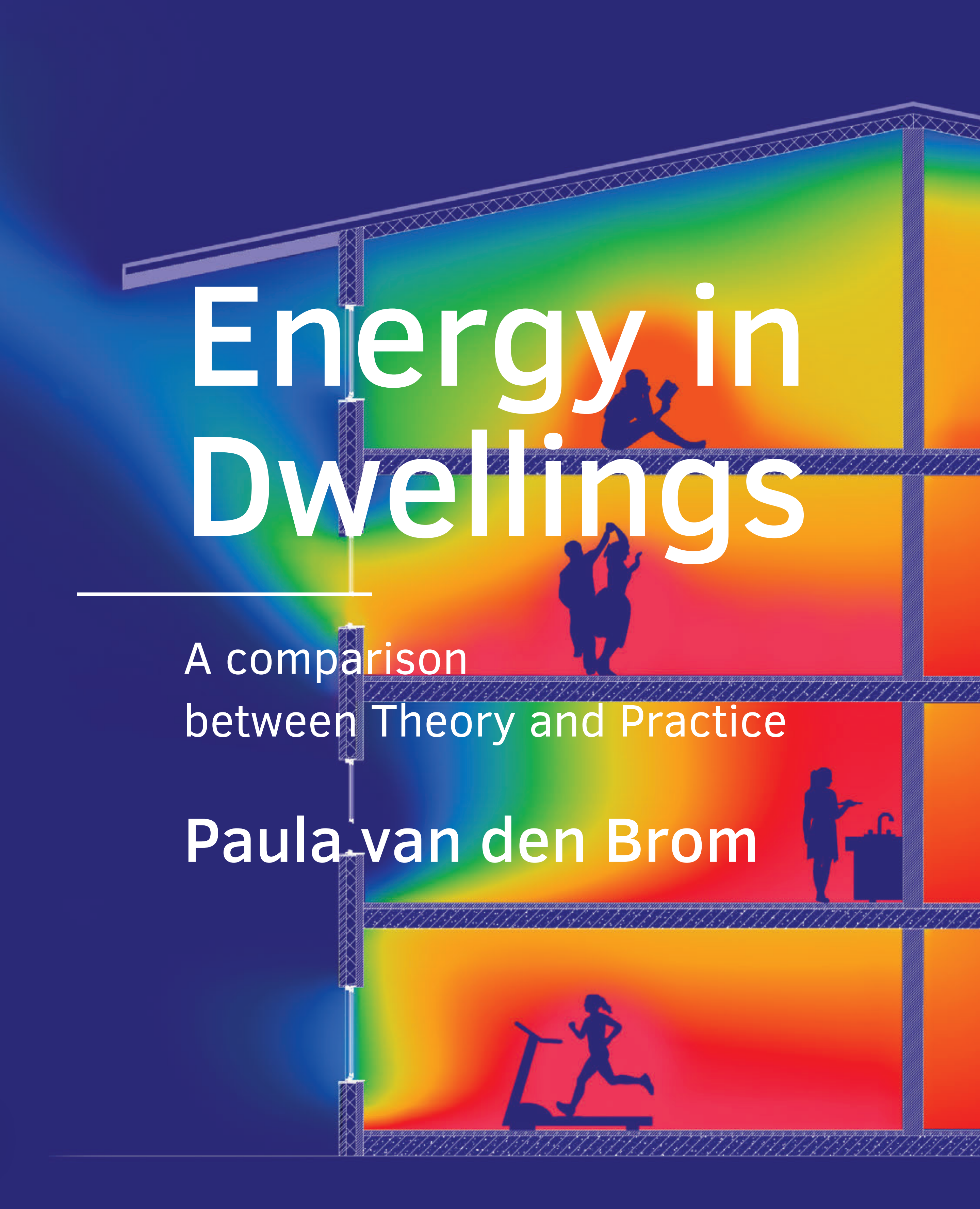
Energy in Dwellings

A comparison between Theory and Practice

Paula van den Brom



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Energy in Dwellings

A comparison between Theory and Practice

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by

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Summary

Reduction of energy consumption is currently high on the political agenda of many countries. Because buildings consume a significant amount of the total energy consumption they form a big energy saving potential. For this reason the EPBD was introduced. This directive introduced a mandatory energy performance certificate for all buildings in Europe (in the Netherlands implemented as energy label). The initial aim of this directive was to make people aware of the energy efficiency state of the building that they buy or rent.

Although the initial aim of the energy performance certificate was to create awareness, it is currently also used for other purposes (e.g. monitoring energy saving progress, setting up energy saving action plans, to calculate payback times and to set energy saving targets). However, a tool used for those purposes should predict energy consumption fairly accurate and that is not the case for the energy certificate.

Due to the increased availability of more details building energy consumption data previous research in many European countries (e.g. Netherlands, France, Denmark, United Kingdom) has shown that there is a discrepancy between predicted and actual energy consumption. The discrepancy between predicted and actual energy consumption is often referred to as the energy performance gap (EPG). . One of the main problems of these EPG is that energy saving measures often do not result in the expected energy savings. Nevertheless, theoretical energy consumption calculations are widely used and their use is increasingonly

The occupant is often blamed for the EPG, because their behaviour is not taken into account in the theoretical calculation. The calculation models make use of a standardized occupant behaviour (indoor temperature, ventilation rate and use of domestic hot water are the same in every calculation).

Almost all studies about the energy performance gap assume or prove that occupants have a significant influence on it. However, the amount of influence is unclear. Some studies found proof for 4.2%, others for 51% . The relationship of the energy performance gap with building characteristics is studied significantly less frequent.

This thesis aims to determine the extent to which building characteristics and residents explain the gap between theory and practice concerning building energy consumption, and to investigate if it is possible to reduce this gap.

Research method

Large databases are used to determine the relationship of occupant and building characteristics with the difference between theory and practice of residential energy consumption. The databases contained building characteristics, occupant characteristics, theoretical and actual annual energy consumption data on a household level. Primarily data from the Netherlands is used; for the third part of the research also Danish data was available. The data is used for statistical analysis to determine the relationships of the difference between theory and practice with occupant and building characteristics.

First statistical analyses are carried out on cross-sectional data with information of 1.4 million dwellings to define the relationship of occupant and building characteristics with the energy performance gap. This is done by analysing different household groups and by analysing the highest and lowest energy consuming groups.

Second, the biggest consequence of the energy performance gap is investigated: the gap between expected energy savings and actual energy savings after a thermal renovation. This has been done by analysing the actual and theoretical energy consumption before and after renovation of almost 90,000 renovated houses in the Netherlands. Only houses that were occupied by the same household before and after renovation were taken into account.

Third, because the results of those two studies show that the difference between theory and practice has a relationship with both building and occupant characteristics, the third part of this research investigates to which extent building and occupant characteristics are responsible for variances in actual residential energy consumption.

Finally, because the previous three parts showed the complexity of residential energy consumption and it dependence on many direct and indirect factors we could conclude that it is impossible to reduce the energy performance gap on an individual level without changing the calculation method. Nevertheless, literature review showed that simple calculation tools for buildings' energy consumption are an important tool for policymakers. Therefore, the last part of this thesis aims to reduce the performance gap on a housing stock level without changing the calculation method. This is done by calibrating simulation models by using actual energy consumption data.

Results

Can analysing building characteristics and household groups provide better insight into the energy performance gap?

The first part of this thesis shows that analysing specific household types and building characteristics can contribute to a better understanding of the influence of the occupant on actual energy consumption and the energy performance gap.

The analyses showed that single person households consume the least energy for heating per square meter and households with families consuming the most. For low energy efficient houses (label D-G) family households have the smallest energy performance gap, while for higher energy efficient houses (label A-C) single person households have the smallest gap. This indicates that there is no direct relationship between the performance gap and occupant characteristics or there are other factors that have a higher influence on the performance gap. Analysis of the highest and lowest 10% consumers groups can help policymakers to choose the right target groups for their energy-saving policies and campaigns. Single person households occur more often in the low energy consuming group and households with three or more members in the high consuming group. Households without children occur more frequently in the low gas consuming groups. For the income we found that low incomes occur more frequently in the extreme groups (high and low consuming groups) and less in the “average” consuming group. Employed occupants occur more often in the low energy consuming group than unemployed occupants; this indicates that occupancy time has a significant influence on Building’s energy consumption. Analysis of the ventilation system shows that the type of ventilation system is especially important for energy efficient houses. For houses with an energy label F or G the distribution of ventilation systems does not differ significantly for the high, low and average consuming groups. The energy efficient houses show (as expected) that balanced ventilation systems occur more frequently in low consuming groups and houses with natural ventilation systems in high energy consuming groups. This indicates that the type of ventilation systems becomes only important when the building has an energy label higher than F or G.

A comparison of the frequency of each construction year for the high, low and average energy consuming group shows that the frequencies of the construction year of the buildings differ significantly for houses with category A, B and C. The results show that, within one label, older houses occur more frequently in the high consuming groups and more recently built houses occur more frequently in the low consuming groups, despite their equal energy label. This indicates that even if buildings are renovated it seems to be difficult to achieve the same performance as new built houses.

Do occupant and building characteristics have a relationship with the difference between actual and theoretical energy savings after a thermal renovation?

One of the most important consequences of the EPG is the lower-than-expected energy savings after a renovation. Because the first part of the research showed that both building and occupant characteristics have a significant influence on buildings' energy consumption and therewith the EPG, the second part of this research investigates the relationship of building and occupant characteristics on actual energy savings after a thermal renovation. The actual and theoretical energy savings of 90,000 renovated houses with the same occupant before and after renovation were investigated. The analyses were carried out for eleven different renovation measures (varying from single renovation measures to deep renovation measures). The statistical analyses show that although deep renovation measures result in the highest energy savings, they also result in the highest Energy Saving Gap (ESG). Further it was found that the effectiveness of renovations is dependent on the state of the building prior to the thermal renovation. Also a relationship with the type of occupant and the amount of energy saved after a renovation was found. On average renovations of relatively low energy efficient houses result in bigger energy saving gaps than renovations of relatively high efficient houses. Single family dwellings save on average more energy than multifamily dwellings after a thermal renovation. Apart from deep renovations it is impossible to conclude which thermal renovation measure is the most effective because it is dependent on the energy efficiency of the building prior to the thermal renovations, the type of building, income level of occupant and occupancy time. Tailored thermal renovation advice is required to decide on the most effective thermal renovation measures.

To what extent are occupants and building characteristics responsible for the variances in actual residential energy consumption?

Because the previous two research topics showed that both occupant and building characteristics are important factors for the difference between actual and theoretical energy consumption the third part of the research studies to which extent occupants and building characteristics are responsible for the variances in actual energy consumption. This study made use of Dutch and Danish building energy consumption data. It compared the actual energy consumption of the year 2010 and 2015 for groups of houses with the same occupant and houses with different occupants. The results show that both, for the Dutch and Danish case approximately half of the variation in consumption can be ascribed to differences in building characteristics and the other half in differences in occupant behaviour. Variations in residential heating consumption across the years of Dutch social housing can be explained by occupants (49%), the Dutch energy simulation model (theoretical consumption) (20%), and by other physical characteristics that are not taken into account in the building simulation model (32%). For the Danish case, we showed that 48% of the variation in residential heating consumption can be explained by occupants, 27% by the building and 25% by other physical characteristics.

The research also showed that the influences of the occupant on variances in energy consumption are dependent on the characteristics of the building. For example the influence of the occupants is larger for energy efficient house than for energy inefficient houses.

Is it possible to reduce the energy performance gap on a building stock level?

The previous three research parts show that actual residential energy consumption is very complex and different for every household. It is dependent on many parameters, direct and indirect, which are almost impossible to incorporate in simple building calculation models that are often used by policymakers. Nevertheless it is important for policymakers to have simple tools to determine potential energy savings, set energy saving targets, to grant subsidies and to determine which energy saving measures are needed to reduce residential energy consumption. Therefore, the last part of the thesis introduces a method that uses actual energy consumption data and automatic calibration techniques to improve assumptions in building energy simulation models used to assess whole building stocks. Two types of models were tested; the first one being the steady state model used in the Netherlands in the framework of EPBD, the other one being a dynamic model in EnergyPlus. The method was able to reduce the root mean square error of the energy performance gap with nearly 24% for the steady state simulation method, and with 27% for the dynamic simulation method, and, most important, the average energy performance gap in the sample as well as in the control group, disappeared almost completely. Therefore this method has the potential to make building simulation models a more reliable tool for policy makers.

Conclusion

The findings in the previous sections result in the overall conclusion answering the main research question:

Can occupant and building characteristics provide better insights into the difference between theory and practice in residential energy consumption, and is it possible to reduce this difference?

This thesis results in two main conclusions. First, both occupants and building characteristics have a significant relationship with the gap between theory and practice in residential energy consumption and saving. Second, it is impossible to reduce the energy performance gap on an individual level without using more detailed data than the buildings simulation tools that the Dutch government currently uses and is planning to use in 2020 (NTA 8088). However, reducing the average energy performance gap on a building stock level is possible by adapting the assumptions used in building energy simulation models.

In the first part of this study, we investigated the influence of building and occupant characteristics on the energy performance gap. This was followed by an investigation of the gap between predicted and actual energy saving after a thermal renovation. Both show that not only occupants but also the building characteristics play an important role in the difference between theory and practice. An analysis of the variances in actual energy consumption through comparing consumption over the years of houses with the same occupants and houses with changed occupants showed that occupants are currently responsible for almost 50% of the variance and building characteristics for the other 50%.

All of these findings together prove that it is important to continue analysing actual energy consumption to determine real-life home energy use. The results show that the relationships between building and occupant characteristics and actual energy consumption are very complex and therefore difficult – and perhaps impossible – to incorporate in traditional physical building simulation models. The results point to the possibility that conventional physical building simulation models should be completed with data-driven models that make use of e.g. machine learning techniques.

A first step using optimisation algorithms/machine learning techniques and actual energy consumption data in building simulation models was shown in chapter 5 of this thesis. This chapter showed that it is possible to reduce the average energy performance gap significantly by optimising the parameters in the simulation model by using actual energy consumption data of multiple dwellings. The use of actual energy consumption data in combination with optimisation algorithms on multiple buildings, help to improve the assumptions for the simulation method, which reduces the energy performance gap and make the outcomes more reliable. In this thesis a proof of principle is shown, to make the method practically usable more research is needed The method will lead to a better reliability of building energy simulations, which is crucial for (amongst others) policymakers and practitioners to make the right decision regarding energy renovations, subsidies, energy saving targets, and energy saving policies in the built environment.

Samenvatting

Energiebesparing staat tegenwoordig in veel landen hoog op de politieke agenda. Omdat het energiegebruik in gebouwen verantwoordelijk is voor een significant deel van het totaal energiegebruik wordt verwacht dat er een groot besparingspotentieel is in gebouw gebonden energiegebruik. In 2003 werd de “Energy Performance of Building Directive” (EPBD) geïntroduceerd om te kunnen meten hoe energie-efficiënt een gebouw is. Deze richtlijn introduceert onder andere een verplicht energieprestatiecertificaat voor alle gebouwen in Europa. Het doel van deze richtlijn was om mensen bewuster te maken van de energie efficiëntie van het gebouw dat ze kopen of huren.

Om het energieprestatiecertificaat te bepalen wordt eerst een theoretisch energiegebruik berekend. Hoewel het energieprestatiecertificaat in eerste instantie bedacht is om bewustzijn te creëren, wordt het tegenwoordig ook gebruikt voor andere doeleinden. (bijvoorbeeld: monitoren van energiebesparing, of stellen van energiebesparingsdoelen en actieplannen en voor het berekenen van terugverdientijden). Voor een tool die op die manier gebruikt wordt is het belangrijk dat het energiegebruik relatief accuraat wordt voorspeld, wat op dit moment niet het geval is.

Verschillende onderzoeken hebben aangetoond dat er grote verschillen zijn tussen het werkelijk en theoretisch energiegebruik. Omdat de berekening van het energieprestatiecertificaat uitgaat van een standaard situatie en daarom geen rekening houdt met verschillen in gebruikersgedrag (bijvoorbeeld: gewenste binnentemperatuur, ventilatiegedrag en gebruik van warm tapwater) wordt het verschil tussen werkelijk en berekend energiegebruik vaak toegeschreven aan verschillen in gebruikersgedrag.

Bijna alle onderzoeken naar het verschil tussen werkelijk en theoretisch gebruik concluderen dat de gebruiker een significante invloed heeft op het verschil, maar de hoeveelheid invloed is onduidelijk. Sommige studies vonden bewijs voor 4.2% van het verschil in werkelijk en theoretisch gebruik en andere onderzoeken vonden dat de gebruiker voor 51% verantwoordelijk is. Het verschil in theoretisch en werkelijk energiegebruik in relatie met specifieke gebouwkarakteristieken is veel minder onderzocht. Het is onduidelijk in hoeverre het verschil is toe te schrijven aan de gebruiker en in hoeverre tot andere gebouw gerelateerde aspecten.

Dit proefschrift heeft als doel vast te stellen in hoeverre de gebruiker en gebouwkarakteristieken een relatie hebben met het verschil tussen werkelijk en voorspeld energiegebruik in een woning en het onderzoekt of het mogelijk is om het verschil tussen werkelijk en theoretisch verbruik te verkleinen zodat het theoretisch energiegebruik een beter hulpmiddel wordt voor onder andere beleidsmakers.

Onderzoeksmethoden

In dit onderzoek wordt gebruik gemaakt van grote databases om te vergelijken wat de relatie van gebruikers en gebouwkarakteristieken is met het verschil tussen werkelijk en theoretisch energiegebruik in een woning. De databases bevatten informatie over gebouwkarakteristieken, gebruikerskarakteristieken, theoretisch en werkelijk energiegebruik op een individueel woningniveau. Er wordt voornamelijk gebruik gemaakt van Nederlandse data; alleen voor het derde deel van dit onderzoek was ook data uit Denemarken beschikbaar. De relatie van gebruikers en gebouwkarakteristieken met het verschil tussen werkelijk en theoretisch gebruik geanalyseerd met behulp van verschillende statistische analyse methodes. De eerste statische analyses zijn uitgevoerd op cross-sectionele data met informatie van bijna 1,4 miljoen woningen. In deze analyse is de relatie van gebruikers en gebouwkarakteristieken met het verschil tussen werkelijk en theoretisch gebruik onderzocht. Dit is gedaan door het analyseren van verschillende huishoudgroepen en door het analyseren van groepen huishoudens die behoren in de 10% hoogste en 10% laagste energiegebruikersgroepen.

Daarna is een van de grootste consequenties van het verschil tussen werkelijk en theoretisch verbruik onderzocht: lager dan verwachtte energiebesparingen na een thermische renovatie. Het energiegebruik voor en na de renovatie van bijna 90.000 gerenoveerde woningen in Nederland is geanalyseerd. Belangrijk aspect van dit onderzoek is dat enkel woningen met dezelfde bewoner voor en na de renovatie zijn meegenomen in de analyse om de invloed van bewonersgedrag zoveel mogelijk uit te sluiten.

Omdat de eerste twee onderzoeken aantonen dat het verschil tussen theoretisch en werkelijk energiegebruik niet enkel afhankelijk is van bewoners, maar ook van gebouwkarakteristieken, wordt in het derde deel van dit onderzoek bepaald in hoeverre gebouwkarakteristieken en hoeverre de bewoner verantwoordelijk is voor verschillen in het energiegebruik.

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Omdat de eerste drie onderzoeken allemaal aantonen dat zowel de gebruiker als de gebouwkarakteristieken belangrijke factoren zijn voor het verschil tussen werkelijk en theoretisch energiegebruik, kan geconcludeerd worden dat wanneer er geen enkele informatie over de gebruiker bekend is, het zeer onwaarschijnlijk is dat het werkelijke energiegebruik goed voorspeld wordt. Voorgaand onderzoek heeft aangetoond dat er niet enkel een verschil tussen werkelijk en theoretisch verbruik is op individueel gebouwniveau, maar ook op woningvoorraadniveau. Dit terwijl men zou kunnen verwachten dat die invloed van gebruikersgedrag zichzelf uitmiddelt. Omdat het theoretisch energieverbruik een belangrijk hulpmiddel is voor onder andere beleidsmakers, is het belangrijk dat de resultaten van deze berekening op zijn minst overeenkomen met het gemiddelde werkelijke energiegebruik van een woningvoorraad. Daarom heeft het laatste onderdeel van dit proefschrift als doel om een methode te ontwikkelen waarmee het gemiddelde verschil tussen werkelijk en theoretisch verbruik verkleind kan worden door gebruik van werkelijke energiegebruiksdata en slimme optimalisatie-algoritmes.

Resultaten

Hoe kunnen gebouwkarakteristieken en huishoudgroepen bijdragen aan een beter inzicht in het verschil tussen werkelijk en theoretisch energie gebruik in woningen?

Het eerste deel van dit proefschrift toont aan dat het analyseren van huishoudgroepen en gebouwkarakteristieken in relatie tot het verschil in werkelijk en theoretisch energiegebruik inderdaad kan bijdragen aan het beter begrijpen van het verschil tussen werkelijk en theoretisch gebruik. De analyses laten zien dat eenpersoonshuishoudens minder energie per vierkante meter gebruiken dan huishoudens bestaande uit meerdere gezinsleden. Ook laat de analyse zien dat voor de energie-inefficiënte woningen (label D-G) het verschil tussen theoretisch en werkelijk gebruik het kleinst is voor woningen waar gezinnen wonen en voor relatief energie-efficiënte woningen het verschil het kleinst is voor eenpersoonshuishoudens. Dit wijst erop dat er geen directe relatie is tussen het verschil in theoretisch en werkelijk energiegebruik en bewonerskarakteristieken, of er zijn andere factoren die meer invloed hebben op het verschil. Een analyse van de hoogste en laagte 10% en gemiddelde energiegebruikersgroepen kan beleidsmakers helpen de juiste doelgroep te kiezen voor energiebesparingsbeleid en campagnes. Eenpersoonshuishoudens komen vaker voor in de laagste 10% gebruikersgroep dan in de gemiddelde en hoge gebruikersgroepen. Huishoudens met drie of meer leden komen juist vaker voor in de 10% hoogste gebruikersgroep en huishoudens zonder kinderen komen vaker voor in de laagste 10% gebruikersgroep. Voor het inkomen vonden we dat huishoudens met een laag inkomen vaak voorkomen in de extreme groepen, dus de hoogste en de laagste 10% en minder in de gemiddelde gebruikersgroep. Wanneer de bewoners van een woning een baan hebben, komen ze vaker voor in de lage energiegebruiksgroepen dan de bewoners zonder baan; dit zou kunnen komen doordat mensen zonder baan vaker thuis zijn wat de gebruikerstijd en vaak daarmee het energiegebruik doet toenemen. Als we naar het ventilatiesysteem kijken valt op dat het ventilatiesysteem vooral in energie-efficiënte woningen een belangrijk verschil maakt. Voor woningen met een energielabel F of G is er nauwelijks verschil te zien in de verdeling van het type ventilatiesysteem per energiegebruikersgroep. Voor de meer energie-efficiënte huizen is duidelijk te zien dat een gebalanceerd ventilatiesysteem vaker voorkomt in de 10% laagste energiegebruikersgroep. Woningen met een natuurlijk ventilatiesysteem komen juist vaker voor in de 10% hoogste energiegebruikersgroep. Dit laat zien dat het type ventilatiesysteem belangrijker wordt naarmate de woning een beter energielabel heeft. Een vergelijking van de bouwperiode voor de hoge, lage en gemiddelde energiegebruikers categorieën laat zien dat bij gebouwen met een energie efficiënt label (A-C) het bouwjaar een sterke relatie heeft met de kans dat een woning in een hoog, gemiddeld of lage energiegebruikersgroep hoort. De resultaten laten zien dat oudere woningen vaker in de 10% hoogste energiegebruikers groep horen en meer recent gebouwde woningen vaker in de laagste 10% energiegebruikersgroep. Dit wijst erop dat het moeilijk is om een woning zo te renoveren dat het dezelfde energieprestaties kan halen als een nieuwbouwwoning.

Hebben bewoners en gebouwkarakteristieken een relatie met het verschil tussen werkelijk en theoretische energiebesparing na een thermische renovatie?

Een van de meest problematische gevolgen van het verschil tussen theoretisch en werkelijk gebruik is dat energierenovaties vaak resulteren in lagere energiebesparingen dan verwacht. Omdat het eerste deel van dit onderzoek liet zien dat, de bewoner- en gebouwkarakteristieken beiden een significant effect hebben op energiegebruik in gebouwen, onderzoekt het tweede deel van dit proefschrift de relatie tussen gebruikers en gebouwkarakteristieken op de energiebesparing na een energierenovatie. De werkelijke en theoretische besparing van 90,000 woningen met dezelfde gebruiker voor en na de renovatie zijn onderzocht. In de analyse wordt onderscheid gemaakt tussen 11 verschillende renovatiemaatregelen (variërend van losse renovatie maatregelen tot een combinatie van renovatiemaatregelen). De statistische analyses laten zien dat ondanks dat diepe renovaties resulteren in de hoogste energiebesparing, ze ook resulteren in het hoogste verschil in werkelijke en theoretische energiebesparing. Verder vonden we dat de effectiviteit van een renovatie afhankelijk is van de staat van het gebouw voorafgaand aan de renovatie. Er is ook een relatie met het type gebruiker en de hoeveelheid energiebesparing na een renovatie gevonden. Gemiddeld resulteren renovaties van erg energie inefficiëntegebouwen (energielabel D-G) in een groter verschil tussen werkelijk en theoretische energiebesparing dan renovaties van energie-efficiënte gebouwen. Eengezinswoningen besparen gemiddeld meer na een energierenovatie dan meergezinswoningen Met uitzondering van diepe renovaties (waarbij het hele gebouw energetisch wordt verbeterd) is het onmogelijk te zeggen welke thermische renovatie maatregelen het meest effectief zijn omdat dat afhankelijk is van de staat van de woning voor de renovatie, het type woning, inkomen van de bewoners en de bezettingsgraad van de woning. Daarom is maatwerkadvies noodzakelijk om te bepalen wat de meest effectieve thermische renovatiemaatregel is.

In hoeverre zijn bewoners en gebouwkarakteristieken verantwoordelijk voor de variantie in werkelijk energiegebruik in woningen?

In het derde onderdeel van dit proefschrift onderzocht in hoeverre de bewoners en in hoeverre de gebouwkarakteristieken verantwoordelijk zijn voor de variantie in werkelijk energiegebruik. Deze studie maakt gebruik van zowel Nederlandse als Deense data. We vergelijken het energiegebruik van de jaren 2010 en 2015 met elkaar voor een groep woningen met dezelfde bewoner(s) en voor een groep woningen waar de bewoners verhuisd zijn. De resultaten laten zien dat zowel de Nederlandse als voor de Deense data ongeveer de helft van de variatie in energiegebruik tussen woningen toegeschreven kan worden aan de gebruiker en de andere helft aan gebouw- en omgevingskarakteristieken. Variatie in het energiegebruik in Nederlandse woningen wordt voor 49% verklaard door de bewoner, 20% door het theoretische energiegebruik berekend met de energielabel-methode en 32% door andere fysische karakteristieken die op dit moment niet meegenomen worden in de theoretische berekening. Voor de Deense data vonden we dat de bewoners voor 48% verantwoordelijk zijn voor het verschil in energiegebruik, 27% door gebouwkarakteristieken en 25% door andere fysische eigenschappen. Met dit onderzoek is opnieuw aangetoond dat zowel de bewoner als de gebouwkarakteristieken belangrijke parameters zijn voor het verklaren van het werkelijke energiegebruik. Daarnaast toont dit onderzoek aan dat de invloed van de gebruiker verschilt voor verschillende woning karakteristieken. Zo laat dit onderzoek zien dat de invloed van de gebruiker groter is bij energie-efficiënte woningen dan bij energie-inefficiënte woningen.

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Is het mogelijk om het verschil tussen theoretisch en werkelijk energieverbruik op woningvoorraad niveau te verkleinen?

De vorige drie onderzoekonderdelen hebben aangetoond dat het werkelijke energiegebruik erg complex is en verschilt voor elk huishouden. Het energiegebruik is afhankelijk van veel verschillende parameters, direct en indirect, waardoor het bijna onmogelijk (en misschien ook onwenselijk)is al deze parameters op te nemen in een simpelgebouwsimulatie model. Dit terwijl simpele gebouw simulatie modellen belangrijke tools zijn voor beleidsmakers om de potentiele energiebesparing van de woningvoorraad te berekenen, energiebesparingsdoelen vast te stellen, subsidies toe te kennen en vast te stellen welke energiebesparingsmaatregelen nodig zijn om het energiegebruik in een woning te reduceren. Daarom wordt in het laatste onderdeel van dit proefschrift een methode ontwikkeld die door gebruik van werkelijke energiegebruiksdata helpt het gemiddelde verschil tussen werkelijk en theoretisch energiegebruik op gebouwvoorraadniveau te verkleinen. De methode maakt gebruik van traditionele automatische kalibratietechnieken en werkelijke energiegebruiksdata om daarmee de aannames die in gebouwsimulatiemodellen gemaakt worden te verbeteren, waardoor de het verschil in theoretisch en werkelijk energiegebruik op gebouwvoorraad niveau wordt verkleind. Twee theoretische berekeningsmethoden zijn getest: een statische en een dynamische simulatiemethode. Voor de statische simulatie is dezelfde methode gebruikt als in Nederland gebruikt werd voor het energielabel en voor de dynamische methode is de software EnergyPlus gebruikt. De aannames die geoptimaliseerd werden in de kalibratieprocedure zijn hetzelfde voor beiden methoden en afkomstig uit de Nederlands energielabel methode gebaseerd op de EPBD. De methode was niet alleen in staat om de "Root Mean Square Error" (RMSE) te reduceren met bijna 24% voor de statische methode en 27% voor de dynamische methode, maar liet het gemiddelde verschil tussen werkelijk en theoretisch gebruik ook bijna helemaal verdwijnen. Hieruit kan geconcludeerd worden dat deze methode de potentie heeft om energiesimulatiemodellen voor gebouwen een meer betrouwbare tool te maken voor beleidsmakers.

Conclusies

De bevindingen van de hiervoor beschreven onderzoeken leiden tot het beantwoorden van de hoofdvraag van dit onderzoek:

In hoeverre kunnen de bewoners en gebouwkarakteristieken het verschil tussen werkelijk en theoretische energiegebruik verklaren en is het mogelijk om dit verschil te reduceren?

Dit proefschrift resulteert in twee belangrijke conclusies. Ten eerste: zowel de gebruiker als de gebouwkarakteristieken hebben een significante relatie met het verschil tussen theoretisch en werkelijke energiegebruik en -besparing. Ten tweede: het is onmogelijk om de energieprestatiekloof te reduceren op een individueel gebouwniveau zonder meer gedetailleerde data te hebben dan de gebouwsimulaties die de Nederlandse overheid nu en in de toekomst (NTA 8088) van plan is te gaan gebruiken. Desalniettemin bewijst dit proefschrift dat het reduceren van de energieprestatiekloof op gebouwvoorraadniveau wel mogelijk is door de aannames in gebouwsimulatiemodellen te optimaliseren.

In het eerste deel van dit proefschrift werd onderzocht wat de invloed van gebouw- en gebruikerskarakteristieken op de energieprestatiekloof is. Dit werd gevolgd door een onderzoek naar de kloof tussen voorspeld en werkelijke energiebesparing na een thermische renovatie. Beiden laten zien dat niet enkel de gebruiker, maar zeker ook de gebouwkarakteristieken een belangrijke rol spelen in het verschil tussen theoretisch en werkelijk energiegebruik. De verschillen tussen het energiegebruik van verschillende woningen is onderzocht door het energiegebruik tussen 2010 en 2015 met elkaar te vergelijken voor twee verschillende groepen. De eerste groep bestaat uit woningen met dezelfde bewoner(s) tussen 2010 en 2015 en de andere groep bestaat uit woningen waarbij de bewoners veranderd zijn tussen 2010 en 2015 (bijvoorbeeld door verhuizing). De resultaten van deze analyse laten zien dat ongeveer 50% van de variantie veroorzaakt wordt door de gebruiker en de andere 50% door gebouwkarakteristieken.

Al deze bevindingen samen bewijzen opnieuw hoe belangrijk het is om het werkelijke energiegebruik te blijven monitoren. De resultaten laten ook zien hoe complex het werkelijke energiegebruik eigenlijk is, en dat het misschien wel onmogelijk is om al deze informatie te implementeren in bestaande simulatiemodellen. Daarom zijn alternatieven methoden nodig. De resultaten wijzen in de richting van een combinatie van traditionele gebouwsimulatiemodellen gebaseerd op bouwfysische eigenschappen gecombineerd met data-gedreven modellen die gebruik maken van machine learning technieken.

Een eerste stap van het gebruik van machine learning technieken en werkelijke gebruiksdata is genomen in hoofdstuk 5 van dit proefschrift. Dit hoofdstuk laat zien dat het mogelijk is de gemiddelde energieprestatiekloof te reduceren door de aannames in gebouw simulatie modellen te calibreren met werkelijke energiegebruiksdata. Dit soort technieken kunnen ertoe bijdragen dat traditionele gebouwsimulatiemodellen een meer betrouwbare tool worden dan ze nu zijn. In dit proefschrift wordt enkel getoont dat het principe werkt. Om de methode ook daadwerkelij in praktijk te brengen is extra onderzoek bezig. Dit is van belang omdat betere betrouwbaarheid van deze simulatiemodellen (onder andere) beleidsmakers en mensen in de praktijk helpen bij het maken van de juiste beslissingen omtrent: energie renovaties, subsidies, energiebesparingsdoelen en energiebesparingsbeleid in de gebouwde omgeving.

1 Introduction

1.1 Residential energy consumption

The reduction of energy consumption is currently high on the political agenda of many countries. Worldwide, a total of 13,760 Mtoe of energy is consumed annually, and without any changes this is expected to increase 30% by 2050 [1]. Moreover, approximately 30% of the total energy consumption is for buildings. In 2015, the international climate agreement (the Paris Agreement) was signed by 185 countries, including the EU member states who collectively account for 15% (2,064 Mtoe) of the total world energy consumption [1]. For execution of the climate agreement, the EU agreed to reduce CO_2 emissions by 20% compared to 1990, 40% by 2030, and 80%–95% by 2050 [2]. Dwellings are responsible for a significant amount of the final energy consumption in Europe (25%); hence, it is not surprising that they are of great interest to policymakers, practitioners, and researchers [3].

In the Netherlands, which is the main study area of this thesis, a significant amount of the final energy consumption is used by households (22%). Currently, an average Dutch household uses 1,432 m^3 (13989 kWh) of natural gas and 2,966 kWh of electricity annually (2015)[4]. The majority of Dutch residential energy consumption is used for space heating. Most houses in the Netherlands (85%) use gas boilers as their heating system, with the consequence that natural gas is the main energy source for Dutch households. The majority of the gas boilers are condensing boilers 75% [5]; however, there are still houses with less efficient gas boilers and some even use local gas stoves. Recently, the number of houses connected to district heating and houses with heat pumps have increased, with 11 % [6] of houses connected to a district heating system and almost 3% [7]using a heat pump as a heating system.

1.1.1 Current policies

To fulfil the requirements of the Paris Agreement, the Dutch government prepared the energy report (2016) [8]in which they explain how these CO_2 reductions can be achieved. The report proposes a combination of CO_2 reduction by reducing energy consumption, increasing the number of renewable energy sources, and CO_2 emission trading. Meanwhile, the Dutch government agreed to make the reduction target for 2030 even more ambitious by aiming for a CO_2 reduction of 49% instead of 40% [9]. In December 2018, the concept design of the Climate Agreement for the Netherlands was presented, which describes how the proposed CO_2 reduction targets can be achieved [10]. The concept Climate Agreement contains information about several sectors, one of which is the built environment. Concerning dwellings, the Climate Agreement states that this is the start of transforming the entire housing stock. New buildings will be built (nearly) energy neutral, and existing houses will be renovated by improving their insulation, installing energy efficient heating installations, adding mechanical heating system with heat recovery, improving the air tightness and by using renewable energy sources instead of gas. In total, this should lead to an energy saving of 100PJ [10]. These are not the first measures that the Dutch government has taken to reduce residential energy consumption.

1.1.2 Energy requirements new built buildings

The oil crisis in 1973 increased the awareness of energy consumption. Consequently, the first regulations concerning energy requirements were introduced in 1975. The first regulation about building energy consumption in the Netherlands demanded a minimum R_c-value of 1.3 m^2K/W for roofs and opaque façade elements. Soon afterwards, double glazing became mandatory for living areas. Currently, the minimum R_c-values for dwellings are significantly stricter: 3.5 m^2K/W for ground floors, 6 m^2K/W for roofs, and 4.5 m^2K/W for facades [11]. In 1995 the energy performance coefficient was introduced in the Netherlands [11]. This is a non-dimensional number that reflects the energy performance of a building. The lower the energy performance coefficient, the more energy efficient the dwelling. The coefficient is based on insulation rates, efficiency of building installations, ventilation systems, and physical characteristics of the dwelling. In 1995, the maximum energy performance coefficient was 1.4; currently (2019), the maximum energy performance coefficient for dwellings was reduced to 0.4. In 2020 the Dutch Energy Performance Coefficient will be replaced by “BENG eisen” (Nearly Energy Neutral requirements). Those requirements do not only take the energy demand in account but also the amount of fossil fuel per square meter and the amount of renewable energy sources.

1.1.3 Energy requirements existing buildings

The energy performance coefficient in the Netherlands is developed for newly built buildings, and is used as a tool to steer the energy efficiency of these buildings. For newly built buildings to become more energy efficient, the government reduces the maximum energy performance coefficient, which implies that newly built buildings are required to become more energy efficient when they are built. However, approximately 75% of the housing stock in 2050 has already been built today [12]. This has the direct implication that stricter building regulations only for newly built buildings will not be sufficient to achieve the energy saving targets set by the government. To encourage homeowners to improve the energy performance of existing buildings the European Commission introduced the Energy Performance of Building Directives (EPBD). This directive is developed to make it possible for consumers to make an informed choice that will help them to save energy and money, and also as a tool for EU and individual member states to make a stable environment for investment decisions to be taken [13]. Currently, the directive is also used to promote the use of smart technology in buildings, streamline existing rules, accelerate building renovation, and as a tool to monitor the energy performance of buildings across Europe [14].

The EPBD made it mandatory for every EU country to have an Energy Performance Certificate for buildings that are either sold or rented [14]. Contrary to the Dutch Energy Performance Coefficient, this Energy Performance Certificate is meant for both newly built and existing buildings. The exact calculation method of the EPBD is different for each country. In the Netherlands the Energy Performance Certificate calculation method is a simplified version of the Energy Performance Coefficient. The reason for this simplification is that building characteristics data for existing buildings are not as well documented as they are for newly built buildings; hence, the input for the Energy Performance Certificate is often collected by visual inspection. In the Netherlands, the Energy Performance Certificate is often referred to as the Energy Label, and the method is described in ISSO 82.1 and 82.3[1]. However, for clarity, we give a short explanation of the Dutch Energy label below.

1 *The method described here is the method of the Energy label in 2011. Since 2014 there has been an updated version of the calculation method, but the data used in this thesis is based on the method of 2011.*

The Dutch Energy Label is based on insulation, type of heating system, type of domestic hot water system, type of ventilation system, and airtightness of the building. A simplified heat transfer calculation determines the energy index, and the Energy labels (A-G) are related to the energy index (Table 1.1). The energy index is calculated based on theoretical energy consumption, and indicates the energy efficiency of the house (Eq. 1.1).

TABLE 1.1 Energy index related to Energy label (ISSO 82.1)

Energy Label	Energy Index (EI)
A++	≤0.5
A+	0.51–0.7
A	0.71–1.05
B	1.06–1.3
C	1.31–1.6
D	1.61–2
E	2.01–2.4
F	2.41–2.9
G	≥2.9

$$EI = \frac{Q_{tot}}{155 \cdot A_g + 106 \cdot A_{verlies} + 9560}$$ EQUATION 1.1

EI = Energy Index
Q_{tot}= total energy consumption [MJ]
A_g = Area [m^2]
$A_{verlies}$ = heat loss area [m^2]

The theoretical energy consumption is a combination of energy used for heating, domestic hot water, energy for pumps and ventilators, energy consumption for lighting, and the generation of energy by solar systems and cogeneration systems. The energy consumption for heating is based on a simple annual heat loss calculation, an average indoor temperature of 18 °C, and the energy efficiency of the heating system. Energy for domestic hot water is determined by the assumed number of occupants in the house, which in turn are assumed from the floor area in m^2 and the energy efficiency of the Domestic Hot Water (DHW) system. The entire calculation method can be found in ISSO 82.1 and 82.3 [15].

$$Q_{tot} = Q_{rv} + Q_{tap} + Q_{hulp} + Q_{verl} - Q_{pv} - Q_{wkk}$$ EQUATION 1.2

Q_{tot} = total energy consumption
Q_{rv} = total energy consumption for room heating
Q_{tap} = total energy consumption for domestic hot water
Q_{hulp} = total energy consumption for help energy (e.g. pumps and ventilators)
Q_{verl} = total energy consumption for lighting
Q_{pv} = annual contribution of photovoltaic solar energy system
Q_{wkk} = annual contribution of cogeneration

FIG. 1.1 Explanation calculation method Dutch energy label 2011

As shown in the Energy label calculation method described in Figure 1.1, the energy label is based on the results of a theoretical energy consumption calculation. The calculation method assumes standards for energy related occupant behaviour (temperature settings, ventilation rate, domestic hot water use). Although it is clear that because of this the theoretical energy consumption calculated with this method can only be valid for a standardised situation, it is not always used as such. Theoretical energy consumption is used by policymakers to determine energy saving targets that would be reasonable to achieve, develop energy-saving policies, monitor the energy performance of the housing stock, determine the maximum rent of a house, and to assign subsidies (e.g. STEP subsidy and stimuleringspremie Meer Met Minder). Further, theoretical energy consumption calculation results are used in practice. For example, theoretical calculations are used to determine which renovation measures would be the most effective, and to calculate payback times and energy savings.

Because the Energy Label is not only used as an indicator of the energy efficiency state of a building, it is important that the theoretical energy consumption results at least reflect actual energy consumption fairly accurately. However, currently this is not the case, and large gaps were found between actual and theoretical energy consumption in previous research (see Figure 1.2). This gap between actual and theoretical energy consumption is often referred to as the Energy Performance Gap. One of the main problems of the gap is that energy saving measures will not result in the expected energy savings.

Policymakers are becoming more aware of the energy performance gap, which is also shown in the new norm NTA8800 that replaces the Energy Index and the Energy Performance Coefficient that will be used from 2020 in the Netherlands[16].

This norm starts with a paragraph stating that the calculated energy consumption results will not be similar to the actual energy consumption. According to the norm this is due to occupant behaviour (number of occupants, ventilation behaviour, temperature settings, use of sun shading, maintenance, and settings of appliances), external influences (outdoor temperatures, shading, or obstructions due to adjoining plots) and of the location of the building in the Netherlands [10]. Although it seems that policymakers are more aware of the energy performance gap, the new method described in NTA 8800 results in an outcome of energy consumption in kWh/m^2 per year instead of the dimensionless energy index and energy performance coefficient that are currently used. This change will probably make even more people use the outcome of this calculation as the expected energy consumption of a building.

1.2 The Energy Performance Gap

Figure 1.2 is one of many examples that shows the difference between average actual and theoretical gas consumption per energy label. The Energy Performance gap is detected in many European countires. Numerous explanations can be found for the performance gap. In general, the explanations can be divided into building characteristics and aspects related to occupant behaviour. However, many people assume that the influence of occupants is the most important, because the occupant determines whether a heating system is on or off and how much domestic hot water is consumed [17-19]. Additionally, energy-related occupant behaviour differs significantly between individuals; hence, it is often unknown. Consequently, assumptions about energy-related occupant behaviour have to be made in building energy simulation models. The differences between actual and assumed occupant behaviour have a significant influence on the gap [20]. Therefore, more information is needed to determine the actual influence of the occupant on residential energy consumption. However, studying occupant influence is not a straightforward procedure, because occupants differ considerably from each other.

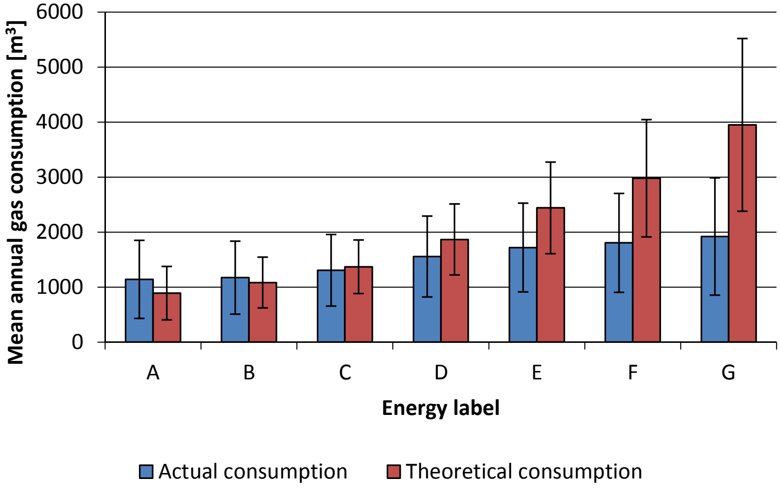

FIG. 1.2 Actual and theoretical gas per m² of dwellings consumption per energy label (Majcen et al., 2013)

Nevertheless, many researchers have already attempted to gain insights into the influence of occupant behaviour on residential energy consumption (among others: Druckman and Jackson [21], O'Neill and Chen [22], Yun and Steemers [23], Brounen, Kok [24], and Alberini and Filippini [25]). The methods and approaches they have used are diverse, and so are the results. The results of those studies do exhibit a common acceptance that occupants influence residential energy consumption; however, the magnitude of that influence remains unclear. For example, Guerra Santin et al. [26] demonstrated that 4.3% of the variance in actual energy consumption for heating can be explained by occupants (based on Dutch data) while Gill et al. [27] found a responsibility of the occupant of 51% (based on UK data).

Investigating the energy-related behaviour of residents is difficult because it is often time-consuming, intrusive for the occupants, and entails privacy-sensitive information. Therefore, these types of studies are often conducted on relatively small samples or based on self-reported behaviour of the resident, which potentially creates biases because people are tempted to provide socially desirable responses.

Many researchers do not use actual energy-related occupant behaviour in their studies, but instead rely on occupant characteristics [21, 24, 26, 28-30]. Occupant characteristics are easier to collect and less sensitive to bias than self-reported behaviour. The previously referred studies have proven that using occupant characteristics is indeed an efficient way to understand actual residential energy consumption, and thus the influence of the occupant on the energy performance gap.

Another factor that makes studying energy-related occupant behaviour complex is that some studies imply that this behaviour is not only influenced by personal preferences and habits, but also by the technical characteristics of the dwellings [31-34]. For example, many researchers found theoretical energy consumption in less-efficient houses to be higher than the actual energy consumption, and the energy consumption of more-energy-efficient houses to be lower than actual usage ([35, 36]). These phenomena are often referred to as the rebound and prebound effects [34].

There are several explanations why the rebound and prebound effects occur. The first assumes that comfort expectations increase when people live in an energy-efficient house instead of an energy-inefficient house. The second is that energy-efficient buildings have more potential to influence residential energy consumption. Energy-inefficient houses, for example, often have natural ventilation systems that are completely dependent on the behaviour of the occupant. More energy-efficient buildings often have natural inlet and mechanical exhausts or balanced ventilation systems that can also be controlled by the occupant, but are a little bit less sensitive for behaviour. Moreover, the increase of low-temperature heating systems in energy efficient-buildings has the consequence that the occupant has less influence due to the relativaly slow reaction time of the system.

As written previously, both the occupant and the technical aspects of a house are expected to have an influence on the energy performance gap. For example, assumptions are made in every building energy simulation model. This is especially true for older houses, because their characteristics are often not documented. Important assumptions that are made include insulation rates of the building envelope and airtightness of the building. However, even for newer buildings it is often unclear if the buildings are built as documented, and mistakes could have been made during the construction process.

Further, tools used for simulation are always a simplification of reality, but some are more simplified than others. Moreover, depending on the purpose of the simulation, the simplification can have an influence on the energy performance gap.

1.3 Problem Statement

Building energy simulation results are widely used by practitioners and policymakers. Previous studies have shown significant differences between actual and theoretical (simulated) energy consumption. This difference makes these simulations less reliable. One of the main problems of these differences is that energy saving measures often do not result in the expected energy savings. Nevertheless, theoretical energy consumption calculations are widely used and their use is increasing [37].

Previous research found that there is not only a discrepancy between energy consumption on individual level but also on a building stock level. Actual energy consumption in energy efficient houses (energy label A-C) is often higher than theoretically expected. Conversely, energy consumption in energy inefficient houses (energy label E-G) is often lower than theoretically calculated. Although the energy label calculation method states that the purpose of this calculation is simply to make the energy efficiency state of buildings comparable, and not to predict residential energy consumption, the outcomes of the calculation are not always used as such.

In practice, the energy label and its associated theoretical energy consumption is used for the design of energy saving policies, assess the feasibility of energy saving targets, assign subsidies, determine the maximum rent, and to monitor progress of the energy efficiency state of buildings [38-40]. The energy saving targets that have to be met are, however, based on actual savings. Therefore, if the gap between theoretical and actual energy consumption is large, the targets will not be met.

Previous studies have shown that residential energy consumption is dependent on building characteristics and occupant behaviour [21-27]. Almost all studies about the energy performance gap assume (or prove) that it is significantly influenced by the occupants. However, the amount of this influence is unclear, with some studies suggesting 4.2% [26] and others 51% [27]. The relationship of the energy performance gap with building characteristics on the energy performance gap has been studied significantly less frequently.

Presently, it is unclear to what extent occupants and building characteristics are related to the energy performance gap. Knowing this information is important, because it informs the users of building energy simulation models, how they can use the simulation outcomes and to what extent they can rely on them. It will also show if and how theoretical energy consumption models can be improved to reduce the energy performance gap. If more is known about the magnitude and cause of the gap, one can manage expectations and perhaps solutions can be found to reduce the energy performance gap to make building energy simulations a more reliable tool.

1.4 Aim & Research questions

The main aim of this thesis is to determine the extent to which building characteristics and residents explain the gap between theory and practice concerning building energy consumption, and to investigate if it is possible to reduce this gap.

This aim is achieved by answering the main research question:

Can occupant and building characteristics provide better insights into the difference between theory and practice in residential energy consumption, and is it possible to reduce this difference?

The main question is answered through four key questions. The first key question is:

1 Can analysing building characteristics and household groups provide better insight into the energy performance gap?

This key question is answered by analysing the relationships of building and occupant characteristics with the energy performance gap.

The main consequence of the energy performance gap is that thermal renovations often result in lower-than-expected energy savings. Therefore the second key question is:

2 Do building and occupant characteristics have a relationship with the difference between actual and theoretical energy savings after a thermal renovation?

To understand the relationship between building and occupant characteristics and the gap between predicted and actual energy savings, theoretical and actual residential energy consumption before and after thermal renovations are analysed.

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Because it is commonly accepted that occupants influence actual residential energy consumption (and therefore the energy performance gap), actual energy consumption should be studied more in depth using the following question:

3 To what extent are occupants and building characteristics responsible for the variances in actual residential energy consumption?

This is investigated by studying residential energy consumption of two different years for a group of houses with the same occupant over time and a group of houses with different occupants over time.

Finally, after answering the first three key research questions, more will be known about the influence of the occupant and technical characteristics on actual energy consumption, energy savings, and the energy performance gap. The last research question investigates if it is possible to reduce the energy performance gap on a building stock level without changing the calculation method by answering the following question:

4 Is it possible to reduce the energy performance gap on a national level by adapting the assumptions in the calculation method?

Together, the answers to these key questions form the answer to the main research question; hence, they will show how theoretical energy consumption results can be used in practice and by policymakers. Additionally, the results will provide new insights into if and how the calculation method can be changed to become a truer reflection of reality.

1.5 Data

This thesis uses several datasets, all based on actual buildings containing annual actual residential energy consumption data, annual simulated energy consumption data, and technical building characteristics data. These building characteristics include the type of heating system, insulation rate, type of ventilation system, type of domestic hot water system, and floor area. This section presents all the databases we used and identify their sources. Additionally, we reflect on the representativeness of the datasets and the studied data. Table 1.2 shows which database is used for which part of the research.

TABLE 1.2 Databases used in this thesis

	Chapter 2	Chapter 3	Chapter 4	Chapter 5
Database	SHAERE & Dutch statistics data	SHAERE & Dutch statistics data	SHAERE, Dutch statistics data, Danish Building and Dwelling Register & Statistics Denmark data	WoON
Year	2014	2010 – 2014	2010 – 2015	2012
Number of investigated cases	1.4 million dwellings	Almost 90,000 dwellings	887,685 dwellings	331 dwellings
Details	Cross-sectional analysis entire database	Renovated houses with the same occupant between 2010 and 2014	Only non-renovated houses with focus on houses with different occupants between 2010 and 2015	Only apartment buildings that use gas as a heating source. Gas consumption data 2010

1.5.1 SHAERE database

The Sociale Huursector Audit en Evaluatie van Resultaten Energiebesparing (SHAERE) database—which in English means “social rental sector audit and evaluation of energy saving results”—is owned by AEDES (the umbrella organisation of Dutch social housing associations). Dutch social housing organisations own 31% of the total housing stock in the Netherlands, and the SHAERE database contains 60% of the social housing stock. Along with building characteristics such as insulation, type of glazing, ventilation, heating, and domestic hot water systems, the SHAERE database also contains a pre-label, the corresponding theoretical energy consumption, and energy index. A pre-label is an energy label that has not been validated by the authorities, but contains the same information as ones that are validated. The advantage of the pre-labels is that they are made as soon as the energy performance of a house is upgraded. This database is updated every year, with the aim to monitor the energy efficiency state of the dwelling stock. The SHAERE databased is used to answer the first three key questions. The SHAERE database from the year 2014 was used for the first key question, SHAERE 2010-2014 was used for the second key question, and SHAERE 2010-2015 was used for the third key question.

1.5.2 Dutch Statistics data

The theoretical energy consumption per dwelling is included in the SHAERE database. However, the actual energy consumption is required to identify the performance gap. For this research, we had access to the actual annual energy consumption data of Dutch households provided by energy companies via the Statistics Netherlands (CBS). This database contains annual actual energy consumption on a household level. We also had access to occupant characteristics data on a household level from the same source. The occupant characteristics data includes income, type of income (from work, benefits, etc.), household composition, number of occupants, occupants above and below the age of 65, number of children, and age of children. Because this data was all available on a household level, we were able to link those databases and execute the analysis.

1.5.3 Danish data

For the third key question, data from both the Netherlands and Denmark were used. The Danish data comes from two sources. Data on building and household characteristics were taken from Statistics Denmark's administrative registers, which covers the full population. These were merged with data on household energy consumption for space heating and hot water from the Danish Building and Dwelling Register (BBR), which is part of the Danish Ministry of Taxation. Heat supply utilities in Denmark are required by law to submit household energy consumption data to BBR, who subsequently compile and prepare data for research and other purposes. The administrative data from Statistics Denmark is accessible in anonymised form through an online server.

1.5.4 WoON energy database

The WoON energy database was used for the last key question of this study. WoON was used instead of the SHAERE database because it is not possible to conduct an optimisation with MATLAB in the protected environment of CBS. The WoON database has an advantage over the SHAERE database in that the actual energy consumption per house is already included in the database. The WoON energy database is based on a survey carried out by the Dutch government (every 5 to 6 years), to gather information on the energy performance of the Dutch dwelling stock. In this thesis, we used the results of the WoON energy survey of 2012, which was the most recently available dataset. The database contains 4800 houses, which should be representative for the entire Dutch dwelling stock. In this study, the actual and theoretical energy consumption per household, the building characteristics, and the occupant characteristics were used for the analysis.

1.6 Research approach

Different research methods are used to answer the key research questions, and in this section we explain them.

The first part of this research is based on descriptive statistics and explains how building characteristics and household groups can shed light on actual and simulated residential energy consumption. This is achieved by comparing actual and theoretical energy consumption of almost 1.4 million houses for different household groups (this is an combination of occupant characteristics[2]) per different energy efficiency group (energy label) of houses. This is followed up by comparing the distribution of building characteristics and occupant characteristics for the highest and lowest 10% of energy consuming groups of the building.

In the second part, statistical analyses are used for almost 90,000 renovated houses to compare actual energy savings and the energy saving gap for different renovation measures or combinations of measures. Only houses with the same occupant for the two compared years are taken into account. Moreover, logistics regressions are used to indicate the building and occupant characteristics that influence the probability on lower-than-expected energy savings after a thermal renovation.

The third part of this research identifies the amount of influence of occupants[3] and technical characteristics of the building on variances in residential energy

2 Occupant characteristics in this thesis includes the following: household composition, age, number of children, employment status and income. The terms occupant characteristics and household characteristics have the same meaning in this thesis.

3 " influence of occupants" as used in chapter 4 of this thesis means a combination of changes in heating consumption of the same occupant over time and changes in heating consumption due to changing occupants.

consumption. This is investigated by comparing the energy consumption of a group of houses with the same occupant in those years and a group with changed occupants. The data are from two different years. The method is adapted from an approach introduced in 1978 by Sonderegger. Compared to Sondereggers study, this method uses significantly improved data from the Netherlands and Denmark. In total, 375,387 non-renovated Dutch houses and 512,393 Danish houses are studied.

Finally, the last key question is answered by introducing a new method based on automated building calibration techniques using optimization algorithms with the aim to reduce the Energy Performance Gap on a building stock level.

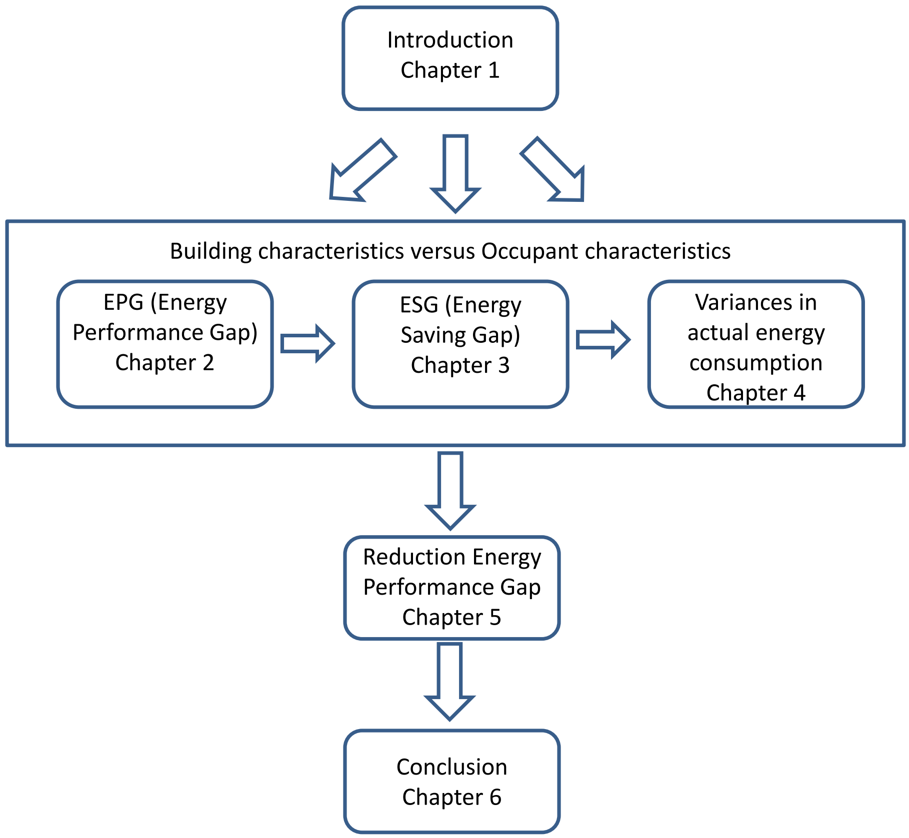

FIG. 1.3 Thesis outline

1.7 Added value of the research

In this section, the scientific and societal relevance of the research is explained.

1.7.1 Scientific contribution

As shown in section 3 of this chapter, many researchers have already investigated the energy performance gap. This thesis builds on this existing knowledge by studying the influence of both technical and occupant influence on the energy performance gap. While many researchers only focussed on one of these two influences, both the energy performance gap and the consequences of the energy performance gap (lower-than-expected energy savings) are investigated in this thesis. Further, the fact that the influence of building and occupant characteristics are not always the same for each situation is considered. The aim is not only to provide a better insight in the energy performance gap but also to develop a method that will reduce this gap. All of this research is executed by using large databases that contain actual and theoretical energy consumption data on a dwelling level of many individual dwellings. The data mainly origins from the Netherlands, however because the databases are large, it is expected that many findings of the research will also be applicable for other countries. Furthermore, this thesis can also be seen as a bundle of examples that shows methods for analysing and reducing the energy performance gap. This thesis adds new knowledge on more accurate building energy modelling

The first two parts of this thesis are empirical studies. In the first empirical study, the relationship between technical characteristics, household groups, and the energy performance gap are discussed. Furthermore, the highest and the lowest 10% of energy consuming houses are analysed per efficiency group. The results indicate which technical characteristics and occupant groups most frequently occur in these groups; this has never been accomplished previously, especially not on such large datasets.

In the second part, pre- and post-thermal renovation energy consumption are analysed with the reason that energy savings are often lower than expected (which is one of the main consequences of the energy performance gap). Because analyses of pre- and post-thermal renovation energy consumption are very rare, especially on such a large scale, this study contributes significantly to the scientific field by testing existing theory and providing new insights into the reasons for lower than expected energy savings after a thermal renovation.

The third part of this study presents an examination of the influence of the occupant and technical characteristics on the variances in actual energy consumption. This is accomplished by applying and extending an “old” method (that compares variances in energy consumption among “movers” and “stayers”) to new, more diverse, and strongly improved data from the Netherlands and Denmark.

The last part of this study describes a new method for reducing the average energy performance gap. The method is based on automated building energy simulation calibration method and improves the assumptions taken in building energy simulations. The effectiveness of the method is proven by applying the method on both steady state and dynamic building energy simulation methods.

1.7.2 Societal contribution

This study contributes to a better understanding of the energy performance gap, a better understanding of how and when to use theoretical energy consumption results, and a better insight into the influence of assumed values in building energy calculation methods. This is of importance for to the scientific field and for society. When policymakers are more aware of the difference between actual and theoretical energy consumption and the difference between actual and expected savings of thermal renovations, they can adapt their expectations concerting energy savings accordingly. Furthermore, knowing which parameters increase and decrease the probability of lower energy savings than expected will help policymakers. Understanding the influence of assumptions built into the theoretical energy calculation method is very important for policymakers, because it can help them to reduce the energy performance gap on a building stock level, which will mean that they will base new policy designs on more accurate calculation results.

Practitioners will greatly benefit from recognising to what extent calculation results can differ from reality. For example, based on the results they can provide a range of payback times instead of a concrete number. Knowing how much of the variance in energy consumption among houses can be explained by the occupant (and how much by the technical characteristics of a building), will help practitioners understand to what extent they can influence residential energy consumption, and to what extent the results can differ from reality. Furthermore, the awareness of the impact of assumptions on the energy calculation results and the energy performance gap is very important for practitioners, because it can stimulate them to provide more tailored advice.

The method that this thesis presents to reduce the energy performance gap on an aggregated level will not only help scientist to make better assumptions in building energy simulation models, but it will also help policymakers to make better official guidelines for assumptions in building energy simulations, which will make those simulations a more reliable tool for policymakers.

1.8 Structure of the Thesis

This research consists of four parts that all contribute to the main aim of this study: determining to what extent building characteristics and residents explain the difference between theory and practice concerning building energy consumption. Additionally, this thesis indicates whether (and how) assumptions made in theoretical energy consumption models can be improved to reduce the energy performance gap on a building stock level (Figure 1.3).

To achieve this main aim, the relationship between technical and resident characteristics and the energy performance gap is investigated. This is done by analysing a large database containing more than 1 million households. In the analysis, the relationship between building characteristics and household groups with actual and theoretical energy consumption is investigated. To obtain more specific insights, the highest and lowest 10% of energy consuming houses are subjected to a more detailed analysis. This is presented in **Chapter 2**.

The next chapter focusses on the biggest consequence of the energy performance gap: lower-than-expected energy savings after a thermal renovation. In this chapter we analyse the actual energy savings and the gap between actual and theoretical energy savings for different types and combinations of thermal renovation measures. In **Chapter 3**, the factors that might influence the probability of lower-than-expected energy savings are also investigated.

Because many people assume that the gap is completely caused by occupant differences, in **Chapter 4** the variances in actual energy consumption are analysed to determine the extent that occupants and technical characteristics influence this variance.

In **Chapter 5,** a method is introduced that automatically calibrates the assumptions for theoretical energy consumption by using actual energy consumption data with the aim of reducing the energy performance gap on a building stock level and to make building energy simulations a more reliable tool.

Together, these chapters will make it possible to answer the main research question: To what extent do technical characteristics and residents influence the energy performance gap in buildings, and what does this mean for the usability of building simulation results? Additionally, these chapters will make it possible to provide policy and research recommendations. These are presented in **Chapter 6,** which is the final chapter of this thesis.

References

[1] iea, *World Energy Outlook 2017*. 2017: International Energy Agency.

[2] EU. *EU climate action*. 2015 [cited 2019 14-02]; Available from: https://ec.europa.eu/clima/citizens/eu_en.

[3] Eurostat, *Final energy consumption by sector*, t2020_34, Editor. 2016: https://ec.europa.eu/eurostat/web/products-datasets/-/T2020_34.

[4] RVO, *Monitor Energiebesparing Gebouwde Omgeving*. 2017, Rijksdiens voor Ondernemend Netherland: Utrecht.

[5] Haas, d.G., d.F. Haas, and v.C. Oel, *Cijfers voortang uitfasering open-verbrandingstoestellen*. 2016: Netherlands.

[6] Menkveld, M., et al., *Monitoring warmte 2015*. 2017, ECN CBS.

[7] CBS. *Warmtepompen; aantallen, thermisch vermogen en energiestromen* 2018 20 December 2018 [cited 2019 25-02-2019]; Available from: https://statline.cbs.nl/StatWeb/publication/?VW=T&DM=SLNL&PA=82380NED&LA=NL.

[8] Zaken, M.v.E., *Energierapport Transitie naar duurzaamheid*, M.v.E. Zaken, Editor. 2016, Rijksoverheid: Den Haag. p. 148.

[9] VVD, C., D66 and ChristenUnie, *Vertrouwen in de toekomst, Regeerakkoord 2017-2021*. 2017: Den Haag.

[10] *Ontwerp van het Klimaatakkoord*, S.-E. Raad, Editor. 2018, Sociaal-Economische Raad: Den Haag.

[11] *Bouwbesluit 2012 (latest revision 17 October 2018)*. 2018.

[12] Visscher, H., et al., *Improved governance for energy efficiency in housing*. Building Research & Information, 2016. **44**(5-6): p. 552-561.

[13] Commission), E.E. *Energy Efficiency - Buildings*. 2015 [cited 2019 10-02-2019]; Available from: https://ec.europa.eu/energy/en/topics/energy-efficiency/buildings.

[14] EC. *Energy Effiicency Buildings*. 2019 [cited 2019 20-2019]; Available from: https://ec.europa.eu/energy/en/topics/energy-efficiency/energy-performance-of-buildings.

[15] ISSO, *Energieprestatie advies woningen*, in *82.3*, ISSO, Editor. 2011: Rotterdam.

[16] NEN, *Nederlandse technische afsparak NTA 8800:2018 (nl) Energieprestatie van gebouwen - bepalingsmethode.* 2018, Koninklijk Nederlands Normalisatie-instituut: Delft.

[17] Janda, K.B., *Buildings don't use energy: people do.* Architectural Science Review, 2011. **54**(1): p. 15-22.

[18] Aydin, E., N. Kok, and D. Brounen *The rebound effect in residential heating*. 2013. 33.

[19] Gram-Hanssen, K., *Efficient technologies or user behaviour, which is the more important when reducing households' energy consumption?* Energy efficiency, 2012. **6**: p. 447-457.

[20] Hoes, P., et al., *User behavior in whole building simulation.* Energy and Buildings, 2009. **41**(3): p. 295-302.

[21] Druckman, A. and T. Jackson, *Household energy consumption in the UK: A highly geographically and socio-economically disaggregated model.* Energy Policy, 2008. **36**(8): p. 3167-3182.

[22] O'Neill, B.C. and B.S. Chen, *Demographic Determinants of Household Energy Use in the United States.* Population and Development Review, 2002. **28**: p. 53-88.

[23] Yun, G.Y. and K. Steemers, *Behavioural, physical and socio-economic factors in household cooling energy consumption.* Applied Energy, 2011. **88**(6): p. 2191-2200.

[24] Brounen, D., N. Kok, and J.M. Quigley, *Residential energy use and conservation: Economics and demographics.* European Economic Review, 2012. **2012**(56): p. 931-945.

[25] Alberini, A. and M. Filippini, *Response of residential electricity demand to price: The effect of measurement error.* Energy Economics, 2011. **33**(5): p. 889-895.

[26] Guerra Santin, O., L. Itard, and H. Visscher, *The effect of occupancy and building characteristics on energy use for space and water heating in Dutch residential stock.* Energy and Buildings, 2009. **41**(11): p. 1223-1232.

[27] Gill, Z.M., et al., *Low-energy dwellings: the contribution of behaviours to actual performance.* Building Research & Information, 2010. **38**(5): p. 491-508.

[28] Guerra Santin, O., *Actual energy consumption in dwellings; the effect of energy performance regulations and occupant behaviour*. OTB, ed. S.U. Areas. 2010, Delft: TU Delft. 237.

[29] Steemers, K. and G.Y. Yun, *Household energy consumption: a study of the role of occupants*. Building Research & Information, 2009. **37**(5-6): p. 625-637.

[30] Yohanis, Y.G., *Domestic energy use and householders' energy behaviour.* Energy policy, 2011. **41**(2012).

[31] Vringer, K. and K. Blok, *The direct and indirect energy requirements of households in the Netherlands.* Energy Policy, 1995. **23**(10): p. 893-910.

[32] Guerra Santin, O., *Occupant behaviour in energy efficient dwellings: evidence of a rebound effect.* Journal of Housing and the Built Environment, 2013. **28**(2): p. 311-327.

[33] Brøgger, M., et al., *Estimating the influence of rebound effects on the energy-saving potential in building stocks.* Energy and Buildings, 2018.

[34] Sunikka-Blank, M. and R. Galvin, *Introducing the prebound effect: the gap between performance and actual energy consumption.* Building Research & Information, 2012. **40**(3): p. 260-273.

[35] Majcen, D., L. Itard, and H. Visscher, *Actual and theoretical gas consumption in Dutch dwellings: What causes the differences?* Energy Policy, 2013. **61**: p. 460-471.

[36] Guerra-Santin, O. and L. Itard, *The effect of energy performance regulations on energy consumption.* Energy Efficiency, 2012. **5**(3): p. 269-282.

[37] Hong, T., J. Langevin, and K. Sun, *Building simulation: Ten challenges.* Building Simulation, 2018. **11**(5): p. 871-898.

[38] Filippidou, F., N. Nieboer, and H. Visscher, *Are we moving fast enough? The energy renovation rate of the Dutch non-profit housing using the national energy labelling database.* Energy Policy, 2017. **109**(Supplement C): p. 488-498.

[39] Sutherlands, G., P.G. Audi, and A. Lacourt, *2016 Implementing the Energy Performance of Buildign directive (EPBD) featuring country reports.* Concerted action - Energy Performance of Buildings, ed. E. Maldonado. 2015, Portugal: European Union.

[40] Hamilton, I.G., et al., *Energy efficiency in the British housing stock: Energy demand and the Homes Energy Efficiency Database.* Energy Policy, 2013. **60**: p. 462-480.

2 Performance Gaps in Energy Consumption: Household Groups and Building Characteristics

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This dissertation deals with the Energy Performance Gap (EPG) and the influence of residential and technical characteristics on it. The EPG is the consequence of the discrepancy between actual and theoretical energy consumption. It is currently unclear to what extent technical characteristics and occupants contribute to this gap. This chapter presents the first exploratory research results of the dissertation, explaining the EPG and its relationship with building characteristics and household groups. This is done by studying a large database (1.4 million houses) containing cross-sectional building, occupant and energy consumption data on a household level. First, the average actual and theoretical energy consumptions (gas and electricity) of different household groups (varying by income level, type of income, and number and age of occupants) are compared for each energy label. After this, we analyse the groups in the top and bottom 10% for energy use to determine which building and occupant characteristics contribute the most to higher or lower-than-expected energy consumption.

ABSTRACT

The difference between actual and calculated energy is called the 'energy performance gap'. Possible explanations for this gap are: construction mistakes, improper adjusting of equipment, excessive simplification in simulation models and, occupant behaviour. Many researchers and governmental institutions think this gap is mainly caused by the occupant. However, only limited evidence exists. Therefore, an analysis is presented of actual and theoretical energy consumption, based on specific household types and building characteristics. Using a large dataset (1.4 million social housing households), the average actual and theoretical energy consumption (gas and electricity) of different household types and characteristics (income level, type of income, number of occupants and their age) were compared for each energy label. Additionally, the 10% highest and lowest energy consuming groups were analysed. It is shown that taking combinations of occupant characteristics into account instead of individual occupant characteristics provides new insights in the influence of the occupant on residential energy consumption. For example: In contradiction to previous studies, low-income households consume more gas per m^2 (space heating and hot water) than households with a high income for all types of housing. Furthermore, the performance gap is not only caused by the occupant, but also by the assumed building characteristics.

KEYWORDS

Household energy, Occupant behaviour; Energy performance; Energy consumption, big data, energy epidemiology, performance gap

2.1 Introduction

In 2002, the EU introduced the Energy Performance of Building Directive (EPBD). The EPBD requires buildings to have an Energy Performance Certificate (EPC), or energy label, when sold or rented. In the Netherlands, the energy label is calculated based on both the building characteristics and modelled heating behaviour of occupants. Through a simplified heat transfer calculation, a theoretical energy usage is determined that relates to an energy label. The theoretical energy usage for residential buildings contains building related energy usage (e.g. energy for heating, hot water, ventilation, lighting in communal areas). Energy use for electrical appliances and lighting in private areas is excluded. The aim of this energy label is to show potential buyers or renters the energy efficiency of their dwelling in an simple and comprehensible way [1]. Apart from this, the labelling system is used by policymakers to set energy saving targets and develop policies. For example, the Dutch social housing associations signed a covenant to renovate their building stock to reach an average energy label B by 2021 and thereby an energy reduction of 33% between 2008 and 2021 [2].

The discrepancies between actual (measured by energy distribution companies) and theoretical energy consumption (as calculated by the energy label) were found by several researchers [3-6]. This set of discrepancies is known as the 'energy performance gap'. Majcen et al. [3] showed that occupants of 'energy-inefficient' buildings consume less gas (for space heating and hot water) than expected, while occupants of 'energy-efficient' buildings consume more than expected. Apart from gas, there is also a gap between theoretical and actual electricity consumption. However, this gap of electricity is expected, because theoretical energy consumption only incorporates building-related energy consumption and not electricity consumption for electrical appliances and lighting. The performance gap for gas consumption is more difficult to explain because it primarily contains energy consumption for heating, which is dependent on multiple factors.

Several researchers found a significant influence of the occupant on residential energy consumption [7-10]. Some researchers even claim that the energy performance gap is primarily caused by occupant behaviour [11, 12]. This suggests that occupants in G label dwellings behave more energy efficiently than occupants in more energy-efficient dwellings. Additionally, occupants in energy-efficient dwellings are assumed to have a higher comfort level than occupants in less energy-efficient dwellings, which could be an explanation for the underestimation of high energy efficient buildings Guerra Santin [13] for example, found that the average indoor temperature in energy-efficient dwellings is higher than in energy inefficient dwellings. This can partly be explained by the so called ‘rebound effect’. The rebound effect is defined by Herring and Sorrell [14] as the increase of energy consumption in services for which improvements in energy efficiency reduce the costs.[4] The opposite of the rebound effect is also found to be true, also known as the ‘prebound effect’ [5].

It is generally known that occupants influence residential energy consumption. However, researchers have so far only been able to use occupant behaviour to explain some of the variance. For example, Guerra Santin [15] found evidence for 3.2%–9.4% of the variance in energy consumption due to occupant behaviour and Majcen [16] for 9.1%. Despite limited evidence for the actual influence of occupant behaviour on residential energy consumption, several organizations and governments have implemented campaigns to change energy behaviours. A clear knowledge base of how inhabitants actually use energy is necessary to improve the effectiveness of energy-saving campaigns, to help policymakers set more realistic energy-saving targets, and to reduce the energy performance gap. However, it is rather time consuming and intrusive to gather actual occupant behaviour data. As there is relatively little explanation for the discrepancy in actual and theoretical energy use, better insight into the influence of the occupant on residential energy consumption is required. Results from in-use building performance research (actual energy consumption) instead of pre-occupancy consumption (theoretical consumption) are essential for the development of energy saving policy instruments [17, 18].

The lack of available occupant data is probably one of the reasons researchers found only limited evidence for the influence of occupant behaviour on the performance gap. Also, most studies that investigate actual energy consumption focus either on occupant behaviour or the building’s characteristics. The rebound effect, however, suggests an interaction between behaviour and building characteristics. Understanding occupant behaviour is essential to predict the energy performance of buildings [19]. Therefore, the present study investigates the research question:

‘Can analysing actual energy consumption by specific household types and building characteristics contribute to a better understanding of the role of the occupant in actual energy consumption and the energy performance gap?’

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4 An example of the rebound effect is when a home is retofitted with insulation or a more efficient boiler. The expected efficiency gain is negated if people increase the hours of space heating and/or raise the internal (winter) temperature. This results in a higher energy use.

This research uses large databases. The first database is the SHAERE database from the umbrella organisation of the Dutch social housing associations. This database contains building characteristics and theoretical energy consumption data from 1.4 million social rented houses in the Netherlands. The other two databases contain occupant characteristics and annual energy consumption data from Statistics Netherland. By combining occupant characteristics and analysis per energy label, it is possible to use large databases to investigate the influence of the occupant on residential energy consumption [20] and identify clear patterns and trends.

This paper is structured as follows. The next section presents an overview of the literature on the influence of occupant behaviour on residential energy consumption along with an explanation of the Dutch energy label system. Next, an overview of the databases and a description of the methods are provided. Then the findings are described. The final two sections contain the discussion and conclusions.

2.2 Existing studies

This section describes findings of previous research regarding the influence of occupant behaviour on residential energy consumption. Findings that are not from the Netherlands are noted as such in the text.

2.2.1 Influence of actual behaviour on energy consumption

Residential energy includes energy for lighting and appliances, cooking, domestic hot water, heating. In the Netherlands, heating consumes the largest share of a building's energy [21]. It is widely recognized that building characteristics influence the actual energy consumption in terms of heating. For example, buildings with a high insulation level consume less energy for heating than buildings with a low insulation level. However, occupant behaviour is also found to have an effect on actual energy consumption for heating. For example, the hours that heating is at its maximum temperature explains 10.3% of the variance in actual energy consumption for heating [22]. The number of hours the radiator is on in a certain room also explains a part of the variance of actual energy consumption for heating (living room 8,8%, bedroom 8.1% and bathroom 5,9%) [22]).

Furthermore, in China the setpoint temperature was found to significantly influence residential energy consumption [23]. Lowering the setpoint temperature by one degree can result in a significant reduction in energy use, similar to roof insulation [24]. The setpoint temperature at night and in the evening has more impact on total energy use than the temperature setting during the day [24].

Appliances are the second main energy consumer in an average Dutch household [21]. Research in the UK found that 19% of energy is consumed by stand-by and continuous appliances (e.g., refrigerators) [25]. In Denmark, 10% of household energy is used solely for stand-by appliances [26]. More frequent use of electrical appliances over previous years has resulted in an increase of electricity consumption. For example, more frequent use of dishwashers has caused a decrease of gas consumption for hand washing but increased electricity use [27].

Energy for domestic hot water is the third highest energy consumer in an average Dutch household [21]. The energy used for domestic hot water is, apart from the domestic hot water system, strongly related to the number of people per household [28]. The majority of domestic hot water is used for showering or bathing. The frequency of showers has been stable in recent years (on average 12 times a week per household) [28].

Energy use for cooking has decreased in recent years. People go out for dinner more often, and delivery and takeaway meals are more common [28].

2.2.2 Influence of occupant characteristics on actual energy consumption

Several studies show a correlation between actual energy consumption and occupant characteristics. Occupant characteristic data is available on a larger scale than occupant behaviour data. Additionally, correlations between occupant characteristics and energy consumption are more usable for policymakers than actual behaviour data. Therefore, many researchers focus on occupant characteristics instead of actual behaviour to study the influence of occupant behaviour on residential energy consumption. The paragraph below describes the findings of previous research on the influence of occupant characteristics on gas and electricity consumption.

Incomes in England were found to be positively correlated with the actual energy consumption in a household [9, 29]. A 1% increase in income increases the total energy consumption by 0,63%, according to Vringer and Blok [30]. The correlation for electricity (r=0.25; p<0.01) was found to be marginally stronger than for gas (r=0.23; p<0.01)[29]. A larger number of household members also results in higher energy consumption, but it decreases the energy consumption per person [4, 23, 24, 29-35].

Age is found to be the most determining indirect effect on heating and cooling energy use in different countries [15, 23, 35, 36]. Occupants between 40 and 50 years demand the highest comfort and also have the highest average net income [34, 37]. Households with young children ventilate less, whereas households with older children ventilate more [15]. Education level has only a very limited impact on residential energy consumption. Higher-educated people set their thermostat for fewer hours on the highest temperature setpoint than lower-educated people [15]. Household size and the presence of teenagers in the house is found to have a significant effect on energy consumption for appliances [38]. Finally tenants are found to have a higher rebound effect than home owners (tenants 31%–49% and home owners 12%–14%).

These results show that studying occupant characteristics is an effective way to investigate the influence of occupants on residential energy consumption. Additionally, studying occupant characteristics instead of actual behaviour data enables us to work with larger datasets.

2.2.3 Other explanations for the energy performance gap

Although occupant behaviour is expected to be one of the main explanations for the energy performance gap, other possible explanations should not be neglected. The insulation level of the building is seldom measured; in most cases it is estimated based on available building documents. As little or no data is available for older buildings, the insulation level of these buildings is determined based on the construction year of the building. Recent research by Rasooli et al. [39] suggests that these assumptions could be an important explanation for a part of the energy performance gap.

Several studies show that the thermal mass of a building contributes significantly to its heating energy demand. This could be another explanation for the performance gap [40, 41]. However, the thermal mass is not taken into account in the theoretical energy calculation of the Dutch energy performance certificate. Therefore, this could influence the discrepancy between actual and theoretical energy consumption.

Additionally, the theoretical energy consumption calculation method that is used for the determination of the energy label, only contains building related energy consumption. However, the actual energy consumption data also includes occupant related energy consumption (e.g., use of electrical appliances).

Finally, the theoretical energy consumption is calculated with a steady state model in this research. This model might be oversimplified. The assumed to be most oversimplified aspects are assumed to be: heat transfer between adjacent rooms with identical air temperature, definition of the combined radiative-convective heat transfer coefficient, different definitions of solar gains (by surfaces or by the air), and Including/excluding solar gains by exterior surfaces such as roofs [42]. Time is not taken into account in the steady state method, so the occupant behaviour is static in the Dutch energy label calculation. Although, relationships between behaviour patterns and occupant characteristics are found in previous research [43]. And using occupancy patterns models have proven to significantly improve the accuracy of the estimation in space heating energy use [44].

2.3 Dutch Energy label

This section describes briefly how the theoretical energy consumption for Dutch dwellings is calculated and how the energy label is determined. Additionally, it describes the assumptions that are made about the occupant in this calculation. The entire calculation and determination method of the energy label can be found in ISSO ISSO [45] (energieprestatie advies woningen).

As mentioned above, the theoretical energy is based on a simplified heat loss calculation. The air tightness, insulation level and ventilation rate are taken into account to define the energy demand for heating. The energy consumption for domestic hot water is based on the assumed domestic hot water use in litres and the energy efficiency of the domestic hot water installation. The theoretical energy consumption only contains building-related energy usage, which is the sum of primary energy for heating, domestic hot water, pumps/fans and lighting in common areas, minus the energy gained from solar panels and cogeneration. This is also important to consider when actual and theoretical energy consumption are compared. The theoretical energy consumption is calculated for a standard situation that assumes the following:

- average indoor temperature of 18 °C;
- average internal heat production due to appliances and people of 6 W/m^2;
- 2620 degree days (equal to 212 heating days with an average outdoor temperature of 5.64°C);
- heating gains from sun, vertical south orientation 855 MJ/m^2 ;
- a ventilation rate based on floor area and type of ventilation system;
- standard number of occupants based on the floor area (Table 2.1);
- 0.61 showers per day per person;
- 0.096 baths per day per person (if there is a bath present).

$$Q_{total} = Q_{space\ heating} + Q_{waterheating} + Q_{aux.energy} + Q_{lighting} - Q_{pv} - Q_{cogeneration}$$

EQUATION 2.1

Qtotal= total theoretical primary energy consumption [MJ]
Qspace heating= total theoretical primary energy consumption for space heating [MJ]
Qwaterheating= total theoretical primary energy consumption for domestic hot water [MJ]
Qaux.energy= total theoretical primary energy consumption for pumps/ventilators [MJ]
Qlighting= total theoretical primary energy consumption for lighting [MJ]
Qpv= total theoretical primary energy gains from solar [MJ]
Qcogeneration= total theoretical primary energy gains from cogeneration [MJ]

TABLE 2.1 Assumed number of occupants in theoretical energy calculation (ISSO 82.3)

Floor area [m^2]	Number of assumed occupants
<50	1.4
50–75	2.2
75–100	2.8
100–150	3.0
>150	3.2

2.4 Data

This section describes the data used for this research and its representativeness.

2.4.1 SHAERE database

The SHAERE (Sociale Huursector Audit en Evaluatie van Resultaten Energiebesparing: in English: social rental sector audit and evaluation of energy saving results) database is owned by AEDES (the umbrella organisation of Dutch housing). Dutch social housing organisations own 31% of the total housing stock in the Netherlands. The SHAERE database contains 60% of social housing stock. Besides building characteristics (e.g. insulation, type of glazing, ventilation, heating, and domestic hot water systems) the SHAERE database also contains a pre-label and the corresponding theoretical energy consumption and energy index. A pre-label is a label that has not been validated by the authorities but contains the same information as the validated one. The advantage of the pre-labels is that they are made as soon as the energy performance of a house is upgraded. The database is updated every year. For this research, the 2014SHAERE database was used.

2.4.2 CBS (Dutch Statistics) data

The theoretical energy consumption per dwelling is included in the SHAERE database, but to identify the performance gap, the actual energy consumption is required. For this research, the authors had access to the actual annual energy consumption data of Dutch households provided by energy companies via the Statistics Netherlands Bureau (CBS). This database contains annual actual energy consumption on a household level. In addition, access was granted to occupant characteristics data on a household level from the same source. The occupant characteristics data includes income, type of income (from work, benefits, etc.), household composition, number of occupants, occupants above and below age 65, number of children, and age of children. This granularity of the data was available at the household level. This allowed the research team to link those databases and execute the analysis.

This is one of the first studies that had access to such a large and extensive database. Addresses and other personally identifiable data were encrypted to ensure the occupants' privacy. Furthermore, the data could only be accessed via a secured server from Statistics Netherlands. The data can only be exported on an aggregated level of at least ten households.

2.4.3 Cleaning data

The raw dataset was filtered before the analysis. First duplicate cases and cases that were not checked in 2014 were removed from the dataset (reduction of 240,330 cases). Next, unrealistic floor areas for social housing in the Netherlands(all dwellings smaller than 15 m^2 and larger than 300 m^2) were deleted (reduction of 20.734 cases). Also all cases with a gas powered heating system that had a gas consumption of zero were removed, as were the cases with an electricity consumption of zero. Finally, all cases with a primary energy use above 4000MJ per m^2 were deleted. The final dataset contained 1,431,019 cases. A correction for climate was applied though the application of degree days. As the energy consumption data of district and block heating were found to be unreliable, all cases with this type of heating system were removed from the dataset.

2.4.4 Household types

Based on occupant characteristic data, 18 household types were formed. These are based on income, household composition, type of income, and age. These household types represent almost 80% of the total number of cases in the SHAERE database (Table 2.2).

TABLE 2.2 Number of household in the 10% highest and lowest energy consuming groups

Energy label	Number of households
A	5018
B	18076
C	30703
D	22003
E	11413
F	6330
G	2442

Household types are not equally distributed among energy labels. Single households and retired couples appear to live more often in A and B label dwellings than in the less energy-efficient dwelling types. Single households that receive state benefits or have a low to average income live more often in dwellings with a low energy label. The same applies for couples with a low or average income and for receivers of state benefits. Households with a high income on average live more often in dwellings with a high energy label. Families with children and a high income live more often in dwellings with an energy label A. Families with a low or average income live less often in buildings with a high energy label (A and B) but also less often in buildings with a low energy label (F and G).

2.4.5 Representativeness of the dataset

This section compares the SHAERE database with the national situation. First, the SHAERE database contains only rental dwellings data, which represents 55.8% of the housing stock [46].

Compared to the national housing stock in the Netherlands, the SHAERE database contains fewer dwellings with an energy label A and B [47]. Compared to the national housing stock, the SHAERE database contains more multifamily dwellings. Fewer buildings were constructed before 1965 and between 1992 and 2005 in the SHAERE database than in the total national stock. More buildings were constructed between 1965 and 1991 in the SHAERE database compared to the national stock.

The average number of household members in SHAERE (1.85) is lower than the overall national average in the Netherlands (2.2). A comparison between the assumed number of occupants in the energy performance calculation and that of the SHAERE database shows that the assumed number is always higher than the actual number.

The average income of the occupants in the SHAERE database is lower than the average income of the total Dutch housing stock. The first to the fifth income percentiles are overrepresented and the higher income percentiles, sixth to tenth, are underrepresented in the SHAERE database.

Occupants over 65 occur more often in the SHAERE database than in the national database (28.9% SHAERE database, 15% Dutch population). Particularly in dwellings with a better energy label, the number of people aged 65 and older is higher in the SHAERE database.

2.5 Method

Gas and electricity consumption per m^2 are studied in this article. This metric was chosen to reduce the impact of variations in floor area. Two methods are used. First, the theoretical and actual average energy consumption for each household type per energy label are compared. The comparison is made on the energy label for two reasons. First, previous research found a relationship between occupant behaviour and the energy efficiency of the dwelling [5, 12]. Second, the data revealed that household types are unevenly distributed among the energy labels. The statistical significance of this comparison is checked with a linear regression.

The second method is a more in-depth analysis of the highest 10% energy consuming group and the lowest 10% energy consuming group of every energy label (Table 2.3). This approach was used because it is expected that the most relevant factors will be more clearly visible in the extreme groups than in the average group, where the factors will be less visible because there is more noise. The assumption is that the observation of the extreme groups will distinguish the relevant parameters more quickly. Both groups are analysed for household type and other occupant characteristics as well as, the building characteristics. The significance of the results is checked with a chi-square analysis. Analyses are conducting with the using IBM SPSS statistics 22 software.

TABLE 2.3 Household types

	Household composition	Age	Children	Age children	Work	Income
1	Single	>65+	No	NA	Retired	NA
2	Single	< 65	No	NA	State benefit	NA
3	Single	< 65	No	NA	Employed	Low
4	Single	< 65	No	NA	Employed	Middle
5	Single	< 65	No	NA	Employed	High
6	Couple	>65	No	NA	Retired	NA
7	Couple	< 65	No	NA	State benefit	NA
8	Couple	< 65	No	NA	Employed	Low
9	Couple	< 65	No	NA	Employed	Middle
10	Couple	< 65	No	NA	Employed	High
11	Family	< 65	Yes	< 12	State benefit	NA
12	Family	<65	Yes	< 12	Employed	Low
13	Family	< 65	Yes	< 12	Employed	Middle
14	Family	< 65	Yes	< 12	Employed	high
15	Family	< 65	Yes	At least one > 12	State benefit	NA
16	Family	< 65	Yes	At least one > 12	Employed	Low
17	Family	< 65	Yes	At least one > 12	Employed	Middle
18	Family	< 65	Yes	At least one > 12	Employed	High

2.6 Results

The results are divided into two parts: gas consumption and electricity consumption. For both parts, first the difference between actual and theoretical consumption is explained and then the highest and lowest energy consuming groups are compared. When interpreting the results, it should be noted that the majority of the residential buildings in the Netherlands (as in this database) use gas for space heating and domestic hot water.

2.6.1 Gas consumption

Comparing actual and theoretical gas consumption per energy label reveals that supposedly energy efficient buildings (energy label A-B) consume more gas than expected. Buildings that are supposed to be inefficient (energy label C-G) consume less gas than expected (Figure 2.1). These findings confirm the findings of Majcen et al. [3].

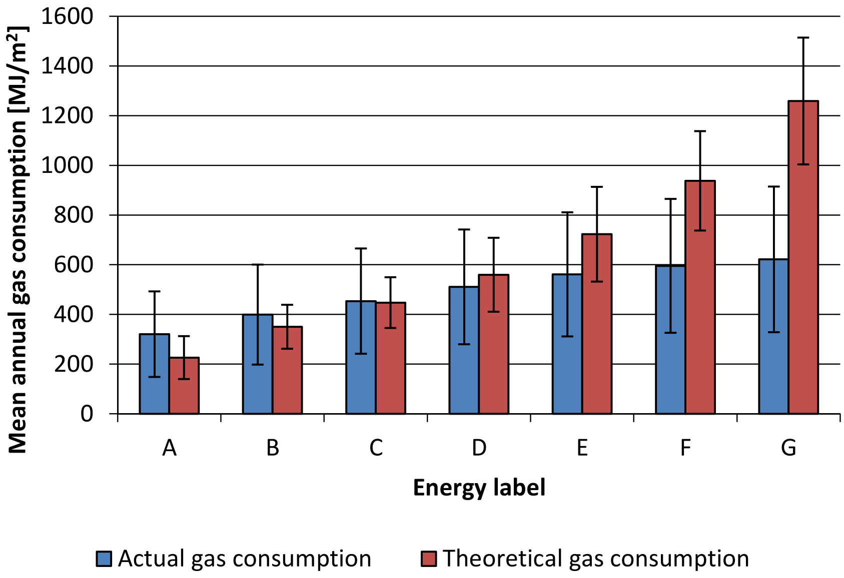

FIG. 2.1 Comparison of actual versus theoretical gas consumption per m2 (error bars show 1sd).

Household types are then added to the comparison between actual and theoretical gas consumption. This provides a better insight on their influence. Figures 2.2 and 2,3 show the results of this comparison. To keep the results section concise, only results for energy labels B and E are shown. The comparison results suggest that actual energy consumption is more influenced by the household type than theoretical energy consumption. This is as expected because type of household is not taken into account in the theoretical energy calculation method.

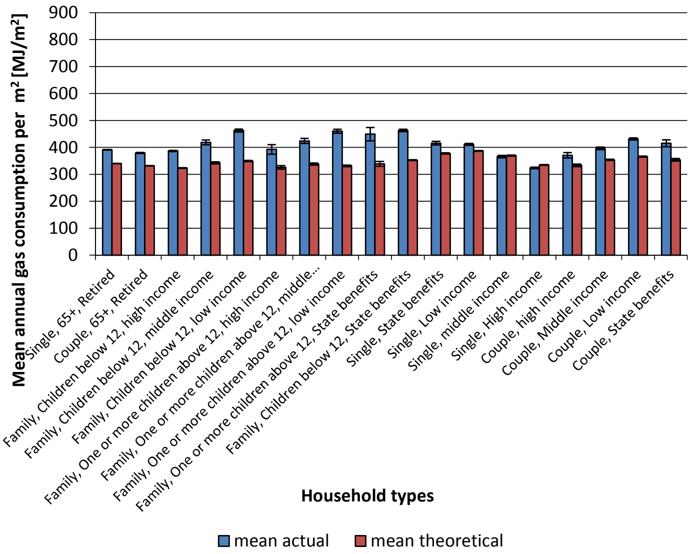

FIG. 2.2 Comparison of mean actual versus theoretical gas consumption per household group – energy label B.

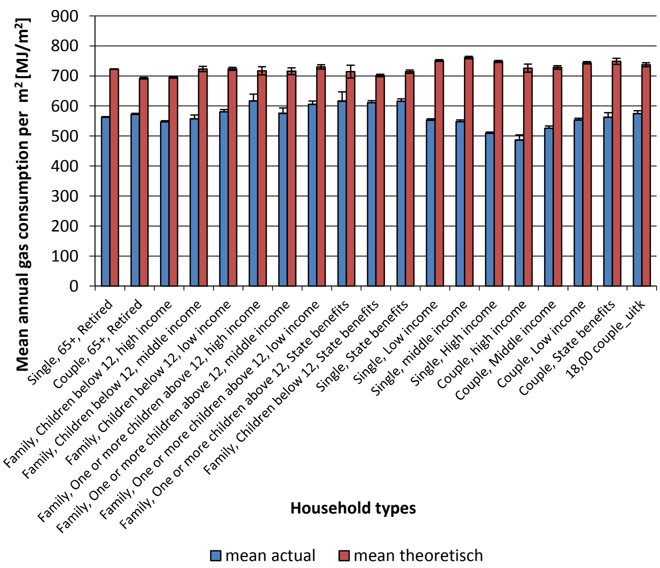

FIG. 2.3 Comparison of mean actual versus theoretical gas consumption per household group – energy label E.

TABLE 2.4 Comparison regression analysis of gas consumption energy (reference dummy variable is Single high income)

	Energy label B R^2=0,011			Energy label B + area R^2=0,082			Energy label E R^2=0,010			Energy label E + area R^2=0,089		
	B	std. B	sig.	B	std. B	sig.	B	std. B	sig.	B	std. B	sig.
constant	11.73		<0.01	18.29		<0.01	16.26		<0.01	24.58		<0.01
Single. 65+. Retired	-0.63	-17.67	<0.01	-1.39	-0.10	<0.01	-0.04	0.00	0.51	-0.24	-0.01	<0.01
Single. State benefits	-0.01	-0.31	0.75	-1.24	-0.07	<0.01	-0.59	-0.03	<0.01	-1.78	-0.08	<0.01
Single. Low income	-0.16	-0.01	<0.01	-1.54	-0.06	<0.01	-0.63	-0.02	<0.01	-1.78	-0.05	<0.01
Single. middle income	-1.36	-0.07	<0.01	-2.43	-0.12	<0.01	-1.82	-0.08	<0.01	-2.76	-0.11	<0.01
Couple. 65+. Retired	-0.95	-0.06	<0.01	-1.02	-0.06	<0.01	-0.73	-0.03	<0.01	-0.07	0.00	0.25
Couple. State benefits	0.04	0.00	0.69	-0.07	0.00	0.44	0.07	0.00	0.59	0.10	0.00	0.42
Couple. Low income	1.01	0.01	<0.01	0.10	0.00	0.60	-0.32	0.00	0.23	-1.17	-0.01	<0.01
Couple. Middle income	-0.46	-7.09	<0.01	-0.69	-0.02	<0.01	-0.61	-0.02	<0.01	-0.68	-0.02	<0.01
Couple. high income	-1.21	-14.23	<0.01	-1.07	-0.03	<0.01	-1.42	-0.03	<0.01	-1.18	-0.03	<0.01
Family. Children < 12. State benefits	1.37	0.04	<0.01	1.21	0.03	<0.01	1.22	0.03	<0.01	0.88	0.02	<0.01
Family. Children < 12. low income	1.45	0.01	<0.01	1.26	0.01	<0.01	1.63	0.01	<0.01	1.11	0.01	<0.01
Family. Children < 12. middle income	0.08	0..00	0.34	0.43	0.01	<0.01	0.05	0.00	0.63	0.24	0.01	0.03
Family. Children < 12. high income	-0.85	-0.01	<0.01	-0.07	0.00	0.64	-0.49	-0.01	0.02	0.04	0.00	0.83
Family. One or more children > 12. State benefits	-0.98	0.03	<0.01	1.45	0.05	<0.01	1.08	0.03	<0.01	1.49	0.05	<0.01
Family. One or more children > 12. low income	1.52	0.01	<0.01	1.91	0.01	<0.01	1.19	0.01	0.06	1..83	0..01	<0.01
Family. One or more children > 12. middle income	0.13	0.00	0.30	0.86	0.02	<0.01	0.71	0.01	<0.01	1.24	0..02	<0.01
Family. One or more children > 12. high income	-0.54	-0.01	<0.01	0.49	0.01	<0.01	-0.19	0.00	0.49	0.95	0..01	<0.01
floor area				-0.08	-0..28	<0.01				-0.10	-0..29	<0.01

Single households have the lowest and family households the highest gas consumption for every energy label. This confirms previous research that a higher number of occupants results in higher gas consumption. Single and family households with a high income consume less gas in almost all cases compared to single and family households that have a low income for every energy label. These findings are confirmed by the regression analysis (Table 2.4) for the majority of the household types. This contradicts the findings of Vringer and Blok [30]. A possible explanation is the use of gas consumption per m² instead of total gas consumption.

It is expected that people with a high income live in houses with a larger area, which they do not heat constantly. However, if the same regression analysis is performed with the floor area of the dwelling, then a negative relationship exists between income and gas consumption, although the impact is smaller (Table 2.4). This suggests that the size of the floor area is only part of the explanation for why households with a high income are often in the low gas consumption group than households with a low income. Another possible explanation is that households with a high income may spend less time at home than households with a low income and, therefore, consume less gas.

As expected, only a limited relationship was found between household type and theoretical energy consumption. The relationship can be traced back to household characteristics.

The largest difference between average actual and theoretical gas consumption in the total sample is found for single households that receive state benefits. The smallest difference is found for families with a high income from work. Analyses that take the energy labels into account show the smallest performance gap for family households in dwellings with a low energy label (D-G). Single households show the smallest gap for dwellings with an energy label between A and C. This means that there is no direct relationship between the performance gap and occupant characteristics or there are other factors that have a higher influence on the performance gap. Another explanation is that the average household type behaviour is dependent on the energy efficiency of the dwelling; e.g. household types behave more energy efficiently in energy inefficient dwellings than in energy efficient dwellings (the prebound effect).

2.6.2 Highest and lowest gas consuming groups compared to the average

To get a better insight into the actual energy consumption, the households with the 10% highest and 10% lowest actual gas consumption per energy label are analysed. The chi-square was used to test the statistical difference in the distribution of the three groups (10% highest energy consumers, 10% lowest energy consumers and 80% average energy consumers).

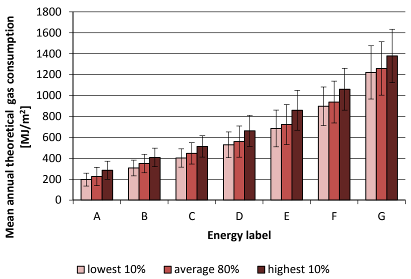

FIG. 2.4 Comparison of highest, average and lowest mean theoretical gas consumption per energy label.

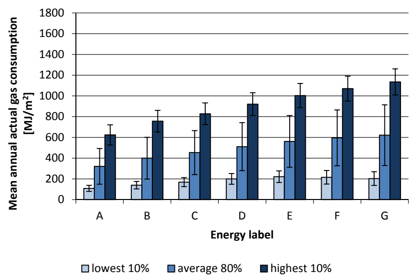

FIG. 2.5 Comparison of highest, average and lowest mean actual gas consumption per energy label.

Figures 2.4 and 2.5 show the average actual and theoretical gas consumption per energy label, the mean lowest 10% and the mean highest 10% gas consuming group. The difference between the highest, lowest and total theoretical gas consuming groups provides evidence that building characteristics influence the actual energy consumption. However, these differences are smaller compared to the actual energy gas consuming groups. This suggests that other factors also influence the actual energy consumption.

A comparison between the average actual and theoretical gas consumption for the lowest 10% gas consuming group shows an almost flat gas use for the actual gas consumption and (as expected) an increasing theoretical energy use as the label increases. The comparison of the actual and average theoretical gas consumption for the highest 10% gas consuming group shows that even the average highest actual gas consuming group consumes less gas than the predicted actual gas consumption.

To understand why residential buildings belong in the highest or lowest actual energy consuming group, a more detailed comparison was made. This involved the comparison of the highest and lowest energy consuming groups for both the building and occupant characteristics.

A comparison of the distribution of household types for the total, highest and lowest gas consuming groups per energy label shows that the distribution of household types is different between groups (Energy label B $\chi^2(34,N=185390)=3747$, $p<0.001$ and energy label E $\chi^2(34,N=115659)=2287$, $p<0.001$) Single households occur more frequently in the lower gas consuming group than in the other groups, independent of label type. With the exception of the single retired household, this group occurs more often in the lower gas consumption group for labels A, B and C, and more often in the higher gas consuming group for labels F and G. This implies that the building characteristics have a larger influence on elderly people than on other household types. An explanation for this phenomenon could be that elderly people are more often at home and, therefore, heat their house longer. However, this explanation cannot be confirmed by this research because actual occupant behaviour is not available. The comparison also shows that family households with children aged 12 years and above occur more often in the higher gas consuming groups for every label type.

Specific occupant characteristics were also compared. In agreement with previous studies, the number of household members shows that households with one member occur more often in the lower gas consumption group, and households with three or more members occur more often in the higher gas consumption group. The difference in distribution is significant (energy label B $\chi^2(8,N=185390)=1832$, $p<0.001$ and energy label E $\chi^2(8,N=115659)=1037$, $p<0.001$).

Households without children occur more frequently in the low gas consuming group and an increased number of children cause the household to occur more often in the higher gas consuming group (Figure 2.6). The distribution difference between groups is significant (energy label B $\chi^2(8,N=185390)=921$, $p<0.001$ and energy label E $\chi^2(12,N=115659)=491$, $p<0.001$).

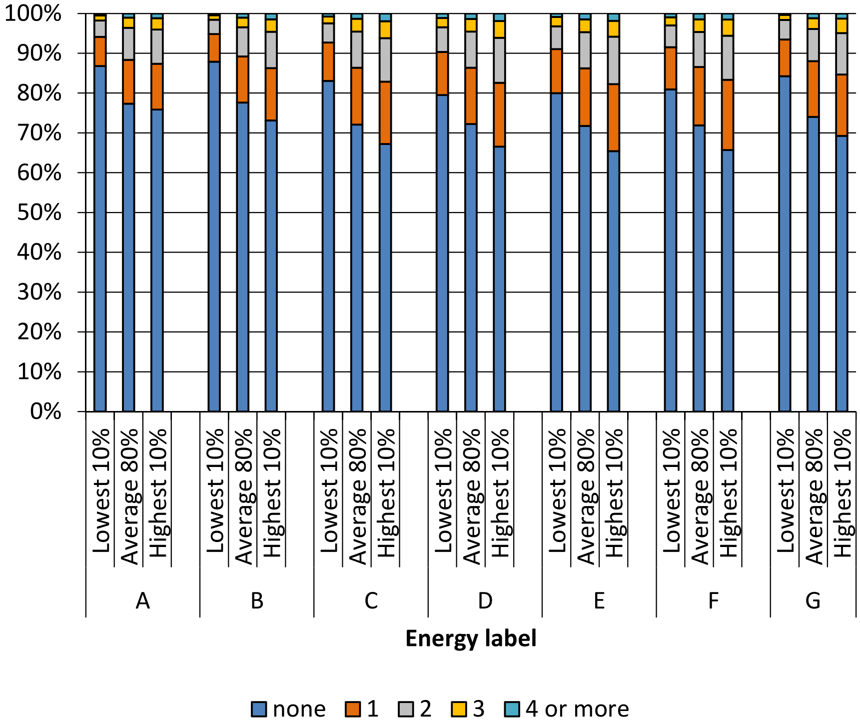

FIG. 2.6 Comparison of the distribution of the number of children in a household for the highest, average and lowest gas-consuming group.

The chi-square test showed a significant difference of the distribution of household incomes between the high, low and average energy consuming groups (energy label B $\chi^2(18, N=185390)=1332$, $p<0.001$ and energy label E $\chi^2(18, N=115659)=838$, $p<0.001$) Lower-income households occur more often in the extreme groups (high and low gas consumption) and higher-income households occur more often in the average group. In the previous comparison per occupant group, however, we found that higher incomes are related to lower gas consumption. A possible explanation is the household type was not taken into account in this comparison. Therefore, other household characteristics (e.g. the number of household members) can therefore influence the results.

If there is at least one household member who is employed, the chance that this household belongs to the low energy consuming group is higher than when no member is employed (energy label B $\chi^2(10, N=185390)=430$, $p<0.001$ and energy label E $\chi^2(10,N=115659)=256$, $p<0.001$). A possible explanation for this could be that the house is occupied less hours per day if someone works. Also other studies found that occupation time influences the residential energy consumption [24, 48].

Apart from the occupant characteristics, Figure 2.4 suggests that building characteristics also influence whether a building belongs to the highest or lowest gas consuming group. Therefore, the distribution of certain building characteristics in the highest and lowest energy consuming group are analysed per energy label group. The influence of heating systems could only be studied with some reservations because the condensing boiler is present in more than 90% of A, B, C and D dwellings. F and G dwellings have a higher mix of heating systems. Analysing the heating systems shows that the gas fire (an appliance that heats and individual room) occurs more frequently in the low energy consuming group, despite a low energy-efficiency rating(energy label B $\chi^2(12,N=185390)=213$, $p<0.001$ and energy label E $\chi^2(14,N=115659)=712$, $p<0,001$).A possible explanation is that gas fire are not able to heat the same floor area as buildings with a central heating system, a suggestion earlier made by Majcen et al. [49].

The distribution of housing type among the highest, lowest and average gas consuming groups is also significantly different (energy label B $\boldsymbol{\chi 2}(16,N=185390)=4702$, $p<0.001$ and energy label E $\chi^2(16,N=115659)=2650$, $p<0.001$). Single family houses occur more often in the high consuming groups, while apartments occur more often in the low gas consuming groups. This can partly be explained by single family houses having a larger building envelope than apartments.

As expected, buildings that are well insulated (R_c value>3.86) occur more often in the low-consuming group and buildings with poor or no insulation (R_c value<2.86) occur more often in the high-consuming group (energy label B $\chi^2(10,N=185390)=2761$, energy label E $\chi^2(8,N=115659)=164$). The results for energy label G were not conclusive. The average *U*-value of the window is lower for the low energy consuming groups (energy label B $\chi^2(10,N=185390)=630$ and energy label B $\chi^2(10,N=115659)=197$)

Mechanical exhaust ventilation and natural ventilation occur more often in the high energy consumption group from label A (Figure 2.7), while a balanced ventilation system occurs more often in the low energy consumption group (energy label A $\chi^2(6,N=185390)=2132$, $p<0.001$, energy label B $\chi^2(9,N=192354)=6779$, $p<0.001$ and energy label C $\chi^2(6,N=115659)=356$, $p<0.001$).Labels B and C have a negligible number of balanced ventilation systems; therefore, mechanical exhaust ventilation occurs more often in the low energy consuming group and natural ventilation in the high energy consuming group. No conclusive results were found for the buildings with an energy label lower than C because they have a low variety in ventilation systems.

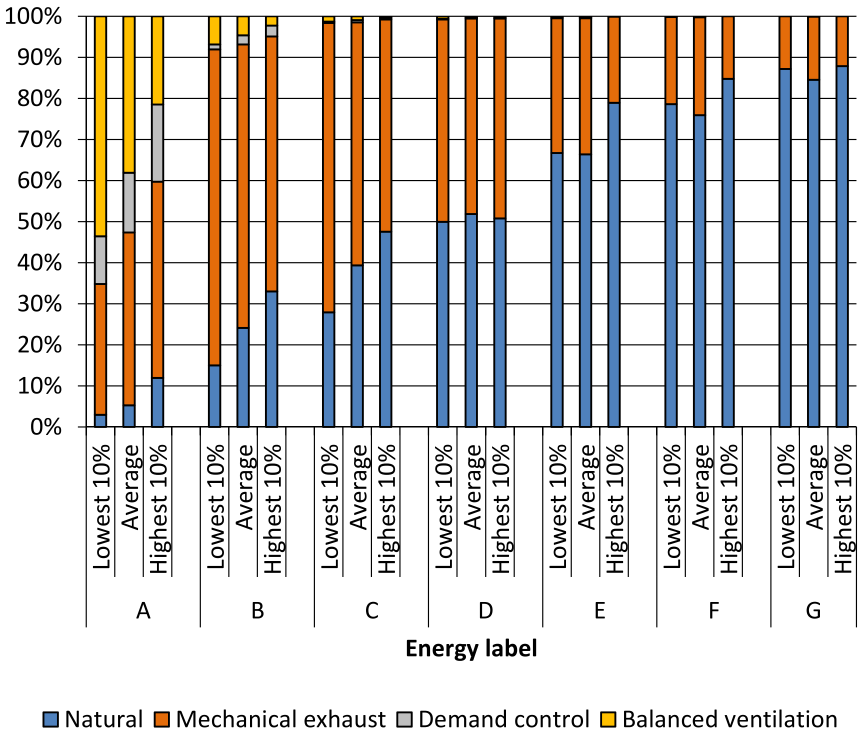

FIG. 2.7 Comparison of the distribution of ventilation systems for the highest, average and lowest gas-consuming group.

Within the A label group, older buildings occur more often in the high gas consuming group than newer buildings (Figure 2.8). It is highly unlikely that buildings built before 1991 had an energy label A from origin, because building regulations did not require it. It is expected, therefore, that the buildings with an older construction year in label A dwellings are renovated. Our findings suggest that it is difficult for renovated buildings to reach the same energy-performance level as newer buildings. Fuel poverty could be another explanation. However, it is less probable, because we found the amount of high income households in this group is five times higher than the amount of low income households.

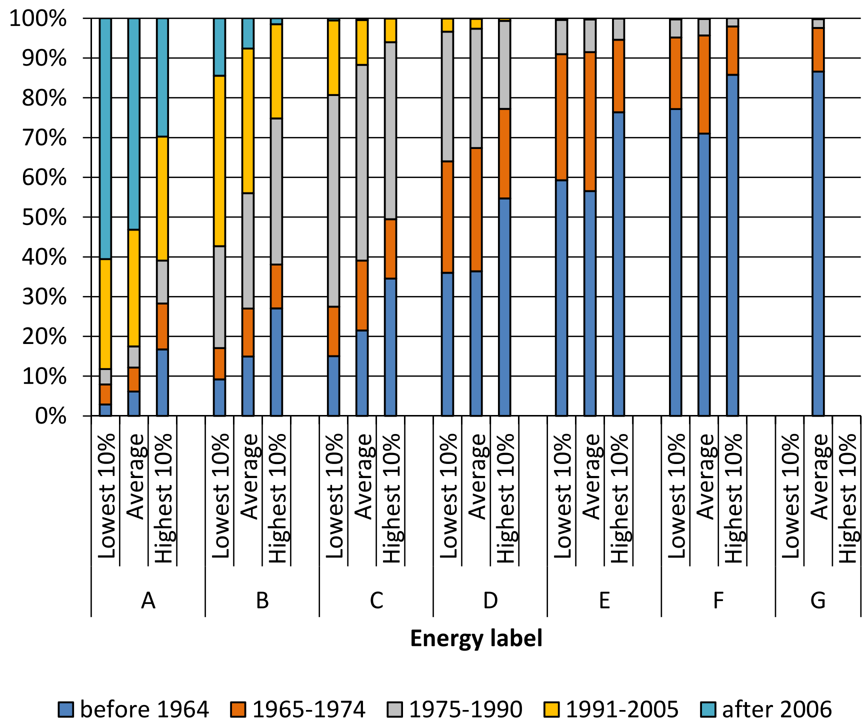

FIG. 2.8 Comparison distribution of construction year for the highest, average and lowest gas-consuming group.

These findings support the general idea that the input for theoretical energy calculations for buildings with a high energy label is more reliable than the input for buildings with a low energy label. More assumptions are likely made about the input for older buildings than for more recent buildings, due to the availability of data.

2.6.3 Electricity

Comparisons of the average actual and theoretical electricity consumption per household type divided per energy label show a difference among household types (Figures 2.9 and 2.10). Single households consume the least electricity per square meter of floor area. Families, especially those with children above 12 years of age, consume the most energy. Families that receive state benefits have a lower electricity consumption than people who have a high income from work. For couples, the electricity consumption for people with state benefits is a little higher than for employed people. Couples with a low income consume relatively the least electricity.

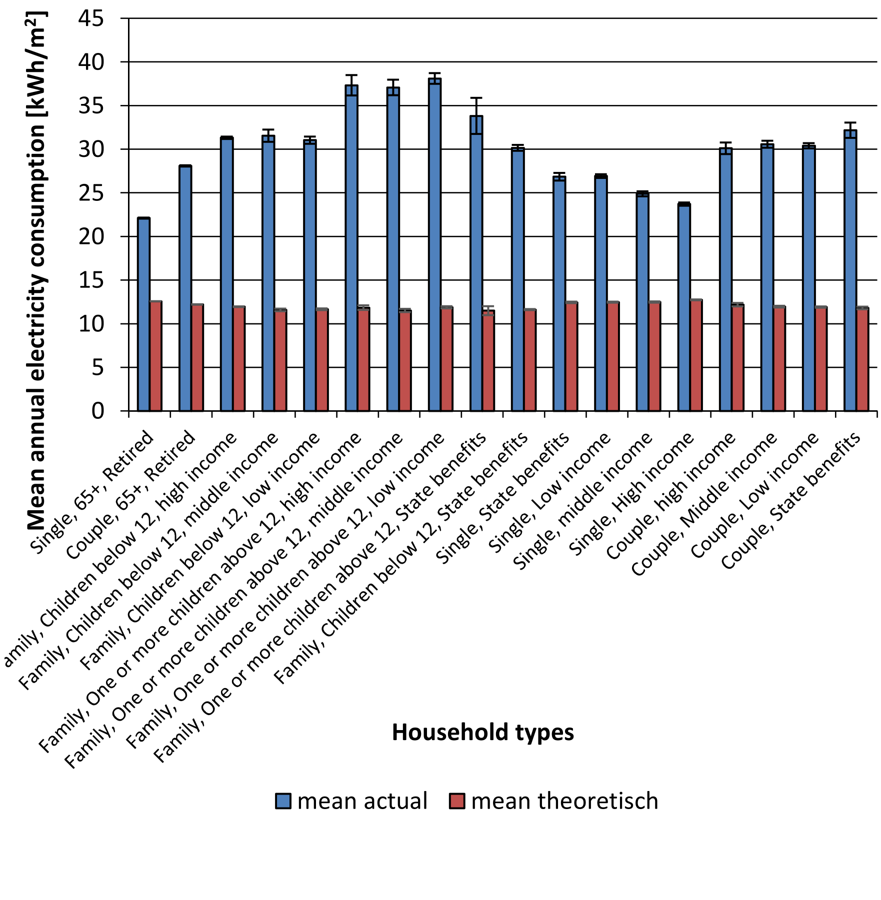

FIG. 2.9 Comparison of mean actual versus theoretical electricity consumption per household group – energy label B.

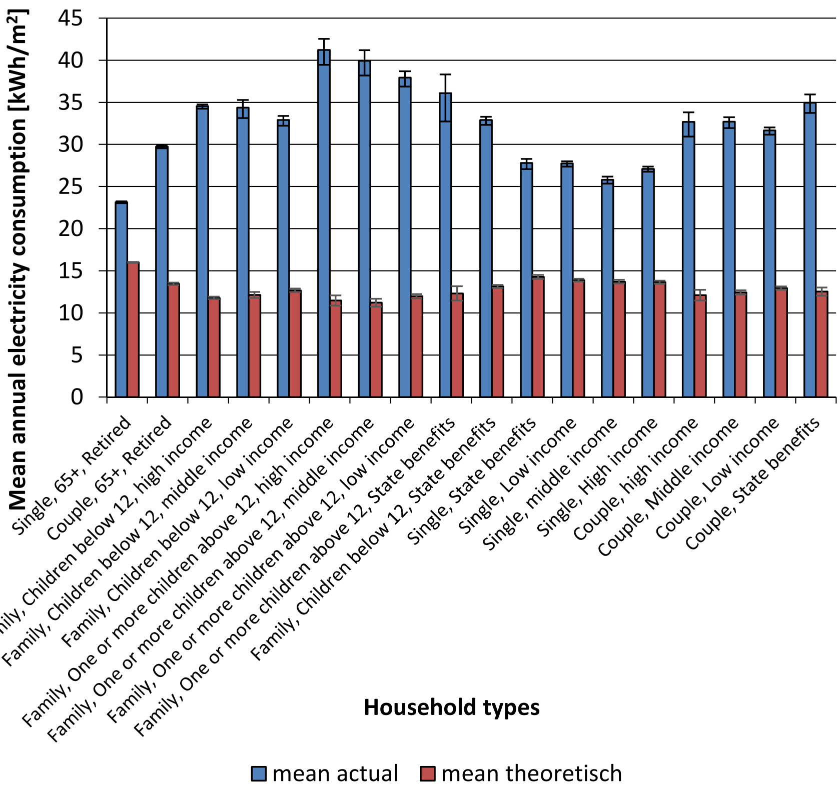

FIG. 2.10 Comparison of mean actual versus theoretical electricity consumption per household group – energy label E.

2.6.4 Highest and lowest electricity consuming group compared to the average

The 10% highest and 10% lowest electricity consumer groups were analysed for electricity consumption. Little difference was found for the influence of the household type per energy label. As a consequence, the energy labels are not taken into account in this analysis. The distribution of household types between the high, low and average energy consuming groups differ significantly ($\chi^2(34, N=55441)=1100756$, $p<0.001$). Single occupant households occur more

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often in the lower-income groups than families. Single retired households occur most frequently in the lowest electricity consuming group. In the higher electricity consuming groups, families and couples occur most frequently, especially families with children older than 12.

Occupants with a high income occur more frequently in the higher electricity consuming groups. Occupants with a low income occur more frequently in the low electricity consuming groups ($\chi^2(18, N=1100756)=15126$, $p<0.001$).

Also a significant difference was found for the distribution of number of people per household ($\chi^2(8, N=1100756)=42472$, $p<0.001$). Single households occur more often in the low energy consuming group and households with two or more members occur more often in the high energy consuming groups.

2.7 Discussion

One of the strengths of this study is the extensive dataset, with 1.4 million dwellings. In contrast to most studies of occupants' influence on residential energy consumption, the present study takes both occupant characteristics and building characteristics into account. This sample only contains buildings owned by social housing organizations in the Netherlands, therefore all dwellings are rental dwellings. Studies in Germany and the Netherlands show that tenants behave differently from housing owners; for example, the rebound effect for tenants is found to be significantly larger than for home owners [12, 50].

The main target group of Dutch housing associations are people with a low income and, therefore, the average income of the sample size is lower than that of the entire Dutch population. Additionally, the average number of household members is relatively low in the SHAERE database compared to the national average. This may have influenced our findings.

In the data filtering process, several possible mistakes were found in both the SHAERE data and the Dutch Statistics datasets. Although the current authors tried to reduce the amount of incorrect data as much as possible, there could still be cases with wrong data. Remaining sources of errors could be due to mistakes in the technical process, such as meter uncertainties, or translation mistakes from one database to the other, and human mistakes during the registering process of the houses in the SHAERE database, which is performed manually.

Housing organisations ought to update their databases each year, but it is not known how accurately or in how much detail they update the state of their building stock. Also, the accuracy of the actual energy consumption data from the Dutch statistics is not known. Additionally, energy companies are only required to report energy consumption every three years. This means that the data that was provided is not necessarily the actual data from 2014, but more likely to be data from 2012 or 2013. Although this is a serious limitation of the dataset, this is the best available data on such a large scale.

The theoretical energy calculation method is only a simplified version of reality. Therefore, it is not realistic to expect it to bridge the energy performance gap at the level of individual households. However, it should be able to reduce the gap for the average energy consumption. For this reason, this research focused mainly on average energy consumption. Although general conclusions can be drawn for specific socio-economic household types, it should be noted that each household is unique, and therefore, the occupants' behaviour can be different from the average.

The occupant characteristics data used in this research do not account for changes within household demographics during the year, e.g. domestic separations, the birth of children and becoming unemployed.

Despite these limitations, this research provides new insights into the influence of occupant characteristics on actual energy consumption and provides several indications for further research.

2.8 Conclusions

The findings of this research show that analysing specific household types and building characteristics contributes to a better understanding of the influence of the occupant on actual energy consumption and the energy performance gap. The analysis of the highest and lowest 10% of consumers can help policymakers to choose the right target groups for their energy saving policies and campaigns. Energy saving advice can also be tailored to specific household types.

The results imply that the building characteristics have a higher impact on elderly people than on younger people. This could be an incentive for policymakers to prioritize building renovations for elderly people.

Single households with a high income are found to have the lowest average energy consumers. A possible explanation could be that they spend less time at home compared to other household types. Therefore, energy saving campaigns focussed on residential behaviour might be not the most effective. However, families with a low income or families that receive state benefits could benefit from energy saving campaigns focussing on the reduction of gas consumption. For the reduction of electricity consumption, this research suggests that focussing on families with high incomes would be the most effective.

The analysis reveals that a disparity between buildings in the same energy group. Buildings constructed more recently consume less energy than older buildings within the same energy label grouping. The energy performance of a new building with energy label A is not the same as a renovated building with an energy label A. This suggests that although renovated buildings reach similar energy performances on paper, these are not achieved in practice. A consequence is that expectations (and financial and other formulations) will need to be different in order to reflect this reality.

The results of this research could also be beneficial for energy consultants and authorities responsible for providing Energy Performance Certificates. Additionally, the findings can help consultants to explain to their clients that energy consumption is not only dependent on physical factors, but also on the occupants' behaviour.

Although a reduction of the performance gap was not a goal, the findings can be used to better interpret the results of energy simulation. People that make building simulations can, for example, inform their clients about the differences between actual and theoretical energy consumption and the possible explanations. This can help clients understand why actual energy consumption is sometimes higher than expected and thus prevent disappointment.

Nevertheless, more research is required. In this research, relationships between certain occupant characteristics and actual energy consumption are found, but the causes of these relationships are not investigated. To explain these relationships, a similar study should be executed on more specific actual behaviour data. A smaller database should be sufficient, for this follow up research.

References

[1] Rijksoverheid. *Energielabel woningen en gebouwen*. 2016 [cited 2016 29-09-2016]; Available from: https://www.rijksoverheid.nl/onderwerpen/energielabel-woningen-en-gebouwen/inhoud/waarom-een-verplicht-energielabel.

[2] BZK, m.v.B.z.e.K., et al., *Convenant energiebesparing huursector*. 2012.

[3] Majcen, D., L.C.M. Itard and H. Visscher, *Theoretical vs. actual energy consumption of labelled dwellings in the Netherlands: Discrepancies and policy implications*. Energy Policy, 2013. **54**: p. 125-136.

[4] Guerra-Santin, O. and L. Itard, *Occupants' behaviour: determinants and effects on residential heating consumption.* Building Research & Information, 2010. **38**(3): p. 318-338.

[5] Sunikka-Blank, M. and R. Galvin, *Introducing the prebound effect: the gap between performance and actual energy consumption.* Building Research & Information, 2012. **40**(3): p. 260-273.

[6] Menezes, A.C., et al., *Predicted vs. actual energy performance of non-domestic buildings: Using post-occupancy evaluation data to reduce the performance gap.* Applied Energy, 2012. **97**: p. 355-364.

[7] Palmborg, C., *Social habits and energy consumption in single-family homes.* Energy, 1986. **11**(7): p. 643-650.

[8] Sonderegger, R.C., *Movers and stayers: The resident's contribution to variation across houses in energy consumption for space heating.* Energy and Buildings, 1978. **1**(3): p. 313-324.

[9] Steemers, K. and G.Y. Yun, *Household energy consumption: a study of the role of occupants.* Building Research & Information, 2009. **37**(5-6): p. 625-637.

[10] Gram-Hanssen, K., *Efficient technologies or user behaviour, which is the more important when reducing households' energy consumption?* Energy efficiency, 2012. **6**: p. 447-457.

[11] Gram-Hanssen, K., *Households' energy use - which is the more important: efficient technologies or user practices?*, in *World Renewable Energy Congress 2011*, EEE, Editor. 2011: Linkoping, Sweden.

[12] Aydin, E., N. Kok and D. Brounen *The rebound effect in residential heating.* 2013. 33.

[13] Guerra Santin, O., *Occupant behaviour in energy efficient dwellings: evidence of a rebound effect.* Journal of Housing and the Built Environment, 2013. **28**(2): p. 311-327.

[14] Herring, H. and S. Sorrell, *Energy efficiency and sustainable consumption. The rebound effect.* Energy, climate and the environment series. 2009, Palgrave Macmillan, UK.

[15] Guerra Santin, O., *Actual energy consumption in dwellings; the effect of energy performance regulations and occupant behaviour*. OTB, ed. S.U. Areas. 2010, Delft: TU Delft. 237.

[16] Majcen, D., *Predicting energy consumption and savings in the housing stock - A performance gap analysis in the Netherlands*, in *Architecture and the Built Environment.* 2016, Delft University of Technology: Delft. p. 224.

[17] Bordass, B., A. Leaman and P. Ruyssevelt, *Assessing building performance in use 5: conclusions and implications.* Building Research & Information, 2001. **29**(2): p. 144-157.

[18] Visscher, H., et al., *Improved governance for energy efficiency in housing.* Building Research & Information, 2016. **44**(5-6): p. 552-561.

[19] Visscher, H., J. Laubscher and E. Chan, *Building governance and climate change: roles for regulation and related polices.* Building Research & Information, 2016. **44**(5-6): p. 461-467.

[20] Hamilton, I.G., et al., *Energy epidemiology: a new approach to end-use energy demand research.* Building Research & Information, 2013. **41**(4): p. 482-497.

[21] Bosseboeuf, D., et al., *Energy Efficiency Trends and Policies in the household and Tertiary Sectors; An Analysis based on the ODYSSEE and MURE Databases*, in *ODYSSEE-MURE project.* 2015, Intelligent Energy Europre Programme of the European Union: http://www.odyssee-mure.eu/publications/br/energy-efficiency-trends-policies-buildings.pdf. p. 97.

[22] Guerra Santin, O., *Behavioural Patterns and User Profiles related to energy consumption for heating.* Energy and buildings, 2011. **43**: p. 2662-2672.

[23] O'Neill, B.C. and B.S. Chen, *Demographic Determinants of Household Energy Use in the United States.* Population and Development Review, 2002. **28**: p. 53-88.

[24] Guerra Santin, O., L. Itard and H. Visscher, *The effect of occupancy and building characteristics on energy use for space and water heating in Dutch residential stock.* Energy and Buildings, 2009. **41**(11): p. 1223-1232.

[25] Firth, S., et al., *Identifying trends in the use of domestic appliances from household electricity consumption measurements.* Energy and buildings, 2007. **40**(2008).

[26] Gram-Hanssen, K., C. Kofod and K.N. Petersen, *Different Everyday Lives: Different Patterns of Electricity Use*, in *ACEEE Summer Study on Energy Efficiency in Buidlings.* 2004, EEE: Sweden.

[27] Dril, T.v., et al., *Energie Trends 2012*, ECN, Energie-Nederland, and N. Nederlnd, Editors. 2012.

[28] ECN, energie-nederland and Netbeheer-nederland, *energietrends 2014*, in *energietrends.* 2014.

[29] Druckman, A. and T. Jackson, *Household energy consumption in the UK: A highly geographically and socio-economically disaggregated model.* Energy Policy, 2008. **36**(8): p. 3167-3182.

[30] Vringer, K. and K. Blok, *The direct and indirect energy requirements of households in the Netherlands.* Energy Policy, 1995. **23**(10): p. 893-910.

[31] Chen, J., X. Wang and K. Steemers, *A statistical analysis of a residential energy consumption survey study in Hangzhou, China.* Energy and Buildings, 2013. **66**(0): p. 193-202.

[32] Jeeninga, H., M. Uyterlinde and J. Uitzinger, *Energieverbruik van energiezuinige woningen; effecten van gedrag en besparingsmaatregelen op de spreiding in the hoogte van het reele energieverbruik*, E. &IVAM, Editor. 2001.

[33] Kaza, N., *Understanding the spectrum of residential energy consumption: A quantile regression approach.* Energy policy, 2010. **2010**(38): p. 6574-6585.

[34] Yohanis, Y.G., et al., *Real-life energy use in the UK: How occupancy and dwelling characteristics affect domestic electricity use.* Energy and buildings, 2007.

[35] Yun, G.Y. and K. Steemers, *Behavioural, physical and socio-economic factors in household cooling energy consumption.* Applied Energy, 2011. **88**(6): p. 2191-2200.

[36] Pettersen, T.D., *Variation of energy consumption in dwellings due to climate, building and inhabitants.* Energy and Buildings, 1994. **21**(3): p. 209-218.

[37] Yohanis, Y.G., *Domestic energy use and householders' energy behaviour.* Energy policy, 2011. **41**(2012).

[38] Brounen, D., N. Kok and J.M. Quigley, *Residential energy use and conservation: Economics and demographics.* European Economic Review, 2012. **2012**(56): p. 931-945.

[39] Rasooli, A., L. Itard and C.I. Ferreira, *A response factor-based method for the rapid in-situ determination of wall's thermal resistance in existing buildings.* energy and buildings, 2016. **119**: p. 51-61.

[40] Bojić, M.L. and D.L. Loveday, *The influence on building thermal behavior of the insulation/masonry distribution in a three-layered construction.* Energy and Buildings, 1997. **26**(2): p. 153-157.

[41] Aste, N., A. Angelotti and M. Buzzetti, *The influence of the external walls thermal inertia on the energy performance of well insulated buildings.* Energy and Buildings, 2009. **41**(11): p. 1181-1187.

[42] Rasooli, A., L. Itard and C. Infante Ferreira, *Rapid, Transient, In-Situ Determination of Wall's Thermal Transmittance.* The REHVA European HVAC Journal, 2016. **53**(5): p. 4.

[43] Kane, T., S.K. Firth and K.J. Lomas, *How are UK homes heated? A city-wide, socio-technical survey and implications for energy modelling.* Energy and Buildings, 2015. **86**: p. 817-832.

[44] Cheng, V. and K. Steemers, *Modelling domestic energy consumption at district scale: A tool to support national and local energy policies.* Environmental Modelling & Software, 2011. **26**(10): p. 1186-1198.

[45] ISSO, *Energieprestatie advies woningen*, in *82.3*, ISSO, Editor. 2011: Rotterdam.

[46] Rijksoverheid. *Woningvoorraad naar eigendom, 2006-2014*. Compendium voor de leefomgeving 2016 [cited 2016 29-09]; Available from: http://www.clo.nl/indicatoren/nl2164-woningvoorraad-naar-eigendom.

[47] RVO. *Compendium voor de leefomgeving.* Energie labels van woningen, 2007 - 20015 2014 [cited 2016 29-09-2016]; Available from: http://www.clo.nl/indicatoren/nl0556-energielabels-woningen.

[48] Majcen, D., L. Itard and H. Visscher, *Statistical model of the heating prediction gap in Dutch dwellings: Relative importance of building, household and behavioural characteristics.* Energy and Buildings, 2015. **105**: p. 43-59.

[49] Majcen, D., L. Itard and H. Visscher, *Actual and theoretical gas consumption in Dutch dwellings: What causes the differences?* Energy policy, 2013. **61**(2013).

[50] Madlener, R. and M. Hauertmann, *Rebound effects in German Residential heating: Do ownership and income matter?* FCN Working paper, 2011. **2/2011**.

3 Actual energy saving effects of thermal renovations in dwellings

Longitudinal data analysis including building and occupant characteristics

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In the previous chapter, we showed that using combinations of occupant characteristics instead of individual occupant characteristics can provide new insights into the influence of the occupant on residential energy consumption. Furthermore, we demonstrated that studying the highest and lowest energy-consuming groups can contribute to a better understanding of residential energy use. However, one of the main consequences of the energy performance gap was not studied: namely, that thermal renovations often result in lower-than-expected energy savings. Therefore, this chapter explains which parameters influence energy savings after a thermal renovation. We do this by studying almost 90,000 renovated houses from which we have actual and theoretical energy consumption before and after renovation. In the analyses, we take into account that the influence of parameters probably differs per thermal renovation measure. Furthermore, we determine to what extent the rebound and prebound effects can explain lower-than-expected energy savings, and we determine the probability of this occurrence.

ABSTRACT

Energy renovations often result in lower energy savings than expected. Therefore, in this study we investigate nearly 90,000 renovated dwellings in the Netherlands with pre and post renovation data of actual and calculated energy consumption. One of the main additions of this paper, compared to previous studies on thermal renovation, is that it only takes dwellings into account with the same occupants before and after renovation, using a large longitudinal dataset. Overall this paper shows new insights towards the influence of the energy efficiency state of a building prior to energy renovation, the type of building, the number of occupants, the income level of the occupants and the occupancy time on the actual energy savings, the energy saving gap and on the probability of lower energy savings than expected. We also investigate if the influence is different per type of thermal renovation measure. Some of the findings are: It is impossible to conclude which single thermal renovation measure is the most effective because this is dependent on the energy efficiency of the building prior to the energy renovation, type of building, income level and occupancy; Occupants with a high income save more energy than occupants with low income; dwellings with employed occupants benefit more from improved building installations than dwellings occupied by unemployed occupants; The prebound and rebound effects are only part of the explanations for lower than expected energy savings; Deep renovations result more often in lower than expected energy savings than single renovation measures but nevertheless they result in the highest average energy saving compared to other thermal renovation measures. The results could be used for more realistic expectations of the energy reduction achieved by thermal renovations, which is important for (amongst others) policymakers, clients and contractors who make use of energy performance contracting, home owners, landlords and (social) housing associations and as a starting point to improve the energy calculation method.

KEYWORDS

thermal renovations, dwellings, longitudinal data, energy saving gap, occupant and building characteristics

3.1 Introduction

Several studies demonstrate evidence of the energy performance gap [1-3]. This gap indicates that, on average, energy-efficient dwellings consume more energy than expected, and energy-inefficient dwellings consume less energy than expected. The consequence of this gap is that another gap arises, the gap between actual and predicted energy savings after energy renovations [4]. In this paper, this new gap is referred to as the energy saving gap (ESG). The ESG is also demonstrated in other studies [5-9]. All indicate that on average, the majority of energy renovations result in lower energy savings than expected.

Many researchers, policymakers and practitioners assume the occupant to be primarily responsible for overestimated energy saving effects [10, 11]. The rebound and prebound effects should explain the discrepancy between expected and achieved savings [4, 12]. The rebound effect can be explained as follows: “Since energy-efficiency improvements reduce the marginal cost of energy services, the consumption of those services may be expected to increase. This increased consumption of energy services may be expected to offset some or all of the predicted reduction in energy consumption” [13]. In practice this means that instead of reducing energy for space heating by improving the thermal characteristics of a house, a renovation might instead lead to increased comfort demand [14, 15]. This would imply that occupants behave less energy efficient in efficient dwellings (rebound effect) and vice versa (the prebound effect) [4]. However, other factors could also explain (part of) the energy saving gap. For example: incorrect assumptions of building characteristics, especially of older buildings [16-18]. The building characteristics of older buildings are not always well documented; therefore, the insulation levels of those buildings are often estimated and might not reflect reality (measuring is time consuming and relatively difficult) [17, 19]. Also mistakes in the construction process could cause (part of) the gap. Another reason for the gap could be the calculation method. A building energy simulation is always a simplification of reality; if the method is oversimplified, then this could result in under- and/or overestimations of building energy consumption.

The energy saving gap has become a concern by several parties, some of the reasons why a better insight in lower than expected savings are desired are: Firstly, policymakers often use expected energy savings as a basis to design new energy saving policies, the ESG makes that the policies do not match the intended goals [20]. An evaluation of the EED [21] mentions that energy renovation plans or guidelines are still lacking in identifying the most effective measures for each climate, country (according to its national energy regulations), type of dwelling, size, age, operation, and maintenance, dwelling envelope, and more. Secondly, clients and contractors who make use of energy performance contracting would benefit from accurate energy saving predictions: "energy performance contracting is a particular form of service contract in which the contractor must ensure, through a binding commitment, that a specified amount of energy will be saved through the project" [22, 23]. Third, home owners, landlords and (social) housing associations might be more willing to renovate if they have a high certainty on the payback time of their thermal renovation measures [24].

Therefore we aim in this study to obtain a better insight into the actual energy savings after thermal renovations, the energy saving gap and the probability of lower energy saving effects than expected. Contrary to most previous studies on thermal renovation, we use longitudinal data instead of cross-sectional data [8, 25-28], including pre- and post-renovation energy consumption data (measured and calculated), as well as building and occupant characteristics data. This longitudinal character prevents possible bias, as changes of occupants are followed in time. The possible bias is also reduced by taking the occupant into account, which is seldom done before in studies towards actual energy savings after thermal renovations[5]. Furthermore, post-renovation studies are often based on relatively small samples because pre- and post-thermal renovation data are scarce, but in this paper we have the availability of a relatively large dataset, including nearly 100,000 renovated dwellings. The research is divided into four parts. In the first part we investigate if building and occupant characteristics (the energy efficiency of the building prior to a thermal renovation, type of building, number of occupants, income level of occupant and the occupancy time) have an effect on the energy savings of different types of thermal renovation measures. We also investigate if the effect is different per renovation measure. This analysis is followed by a similar analysis of the energy saving gap. Then we determine how frequent the prebound and rebound effects occur in the renovated buildings. Finally, we conclude with a detailed logistic regression in which we investigate which factors influence the probability on lower than expected energy savings after a thermal renovation.

The research is structured as follows: In section 2, we provide the state of the art of the research, which includes the calculation method for residential energy consumption. Then, we describe the database and the research method. After this we give a description of how we define thermal renovations in this paper. The results section presents the results of the four different analyses described above. In the discussion section, we explain the advantages and disadvantages of the method and data that we used and how this influences the results, and finally we draw general conclusions.

3.2 State of the art - Actual and theoretical energy consumption and the energy saving gap

In this section we explain the calculation method of theoretical energy consumption used in this paper, the expected/actual energy savings and the energy saving gap.

Since heating is the main energy consumer of dwellings in the Netherlands and because energy consumption for heating has the highest unexplained energy performance gap [26], only the energy use for heating and domestic hot water (dhw) is studied. Because approximately 90% of the Dutch households use gas as a heating source we can, by studying only gas consumption distinguish the energy used for heating and dhw versus the energy used for household appliances. This means that houses that do not use gas as a heating source are removed from the analysis. Energy saving in this paper can therefore be read as gas savings/energy saving for heating. Cooling systems are not common in Dutch households and are therefore not included in the analysis. The expected energy consumption (energy demand) for heating used in this paper is based on the method that the Dutch government uses to define the Energy Performance Certificate. The method is based on a quasi-steady-state calculation (the entire calculation method is described in ISSO 82.3 [29]). To calculate the energy demand for heating the following parameters are taken into accounts: air tightness, insulation levels, ventilation rates, efficiency of the heating system. A normalised number of occupants per m^2 determine together with the efficiency of the dhw system how much energy is required for hot water.

The amount of expected energy saved after a renovation is the difference of the estimated energy consumption before renovation and after renovation (eq 3.1). We correct for building size by using the energy consumption per square meter of floor area, because building-related energy is highly dependent on the floor area of the building [30]. Since we do not know the specific moment of the year the renovation took place, we decided to compare the first year of our database (2010) with the last year of our database (2014) (eq 3.1). This means that energy saving is determined as the gas consumption of year 2010 minus that of year 2014. To make the years comparable a correction for degree days is applied. The amount of actual saving is the amount of energy consumed before the renovation minus the amount of energy consumed after the renovation (eq 3.2). These data are obtained at an address level from Statistics Netherlands (CBS). The energy saving gap is equal to the expected savings minus the actual savings (eq 3.3).

$$fQ_{saving} = fQ_{pre} - fQ_{post}$$ EQUATION 3.1

fQ_{saving}= expected energy savings after renovation [MJ/m^2]
fQ_{pre}= expected gas consumption before renovation (year 2010)[MJ/m^2]
fQ_{post}= expected gas consumption after renovation(year 2014) [MJ/m^2]

$$Q_{saving} = Q_{pre} - Q_{post}$$ EQUATION 3.2

Q_{saving}= actual energy saving after renovation [MJ/m^2]
Q_{pre}= actual gas consumption before renovation (year 2010) [MJ/m^2]
Q_{post}= actual gas consumption after renovation (year 2014) [MJ/m^2]

$$ESG = fQ_{saving} - Q_{saving}$$ EQUATION 3.3

ESG= energy saving gap [MJ/m^2]
fQ_{saving}= expected energy saving after renovation [MJ/m^2]
Q_{saving}= actual energy saving after renovation [MJ/m^2]

3.3 Data

Two different data sources are used in this study. The first one is the SHAERE database, which is from the umbrella organisation of the Dutch social housing companies in the Netherlands (AEDES). The main aim of this database is to monitor the energy efficiency of the social housing stock in the Netherlands. It contains 60% of the social housing stock in the Netherlands, which, comprising 30% of the total housing stock, is relatively large, compared to other countries. This means that the database contains a significant share of all dwellings in the Netherlands. It also contains most of the input variables that are used to calculate the energy performance of dwellings, and these data are present for five consecutive years (2010-2014). The second source is data from Statistics Netherlands (2010-2014) and contains actual annual energy consumption data and occupant characteristics data on a household level. Because of privacy protection we are only allowed to publish the results on an aggregated level (a minimum of 10 cases).

Approximately 90% of the Dutch households use gas as a heating source for their homes [31]. Most households use a combined gas boiler that provides both heating and dhw. Since heating is the main energy consumer of the dwellings and because energy consumption for heating has the highest unexplained energy performance gap [26], we studied only dwellings that use gas as a heating source and electricity consumption is not taken into account (127,183 cases). This means that energy saving in this paper can be read as gas savings.

Dwellings with collective heating systems were deleted from the database because the Statistics Netherlands expressed doubts about the quality of those data. Furthermore, cases with a floor space of over 1000 m^2 and dwellings with gas consumptions higher than 500,000 MJ were discarded from the analysis (150 cases and 10 cases). Statistics Netherlands obtains its actual energy consumption data from energy supply companies, and it is officially only required to collect these data once every three years. Since it is important to have the correct energy consumption in the correct year for this analysis, we deleted the dwellings with the exact same energy consumptions as the previous year (307,975 cases) because it is highly unlikely that a dwelling consumes exactly the same amount of energy every year. To make the actual energy saving data comparable to the predicted energy saving, the energy consumption data were normalized to 2,262 degree days per year which is used as standard in the theoretical calculations. Almost 95% of the occupants, stayed in their dwelling after renovations. To prevent possible bias from change in occupant behaviour as much as possible we excluded all cases where the occupant before renovation was different compared to after renovation (221,165 cases). One could expect that dwellings that are deeply renovated would undergo a change of occupants more often than those in which only one thermal renovation measure is applied, because for deep renovations it is more often necessary that the house is uninhabited. However, from our data, there was no difference in the percentage of changed occupants between the single renovation measures and the deep renovations. Also dwellings in which other renovation measures than mentioned in section 5 or administrative corrections were found are excluded from the analysis (41,597 cases). Finally there were 228,991 cases that didn't have information to identify if a renovation was or was not executed; therefore also those cases are excluded from the analysis, leaving with a total of 235,753 cases. From which 87,513 houses are renovated between 2010 and 2014 (see Figure 3.1).

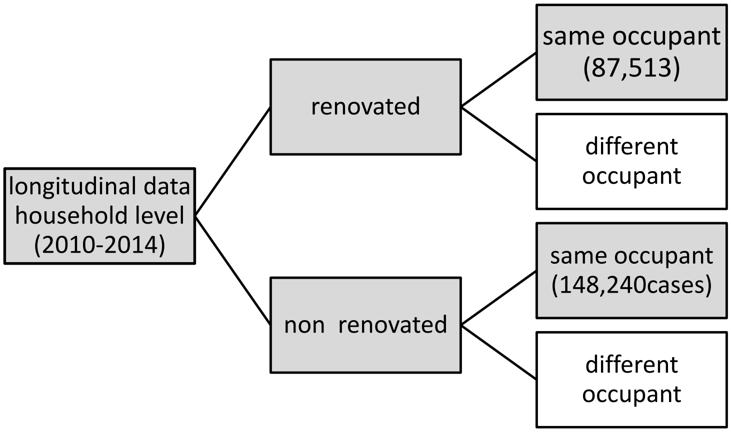

FIG. 3.1 Analysed data

3.4 Methods

First, we used descriptive statistics in which we determine how frequent the thermal renovation measures occur in the database and how frequent this results in lower and higher than expected energy savings. These descriptive analyses should indicate whether thermal renovations indeed result more often in lower savings than expected.

To test whether the savings per renovation measure differ significantly from dwellings that were not renovated, a Kruskal-Wallis test (which is a one-way ANOVA on ranks) with a follow-up pairwise comparison was executed. The Kruskal-Wallis test was chosen instead of a traditional ANOVA because the energy saving data are not normally but leptokurtic distributed. The leptokurtic distribution could make the Type I error rate too low, and consequently the power too high, if a traditional ANOVA was used [32].

When the average energy savings per renovation measure are known, we investigate, as shown in Figure 3.2, whether specific building and occupant characteristics influence the amount of energy saved and if they are different per renovation measure. For these analyses, we execute also the Kruskal-Wallis test. If there are

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only two groups compared, then the Whitney U-test is used which is the non-parametric equivalent of the independent samples t-test. In the second part of the analysis, similar analyses were conducted for the energy saving gap (Figure 3.2).

The following building and occupant characteristics are investigated: the energy efficiency of the building prior to the thermal renovation, the building type, household income, the number of employed occupants and the number of household members. These specific occupant characteristics were chosen for two reasons, namely availability and because previous research or existing theories expect a correlation between those aspects and energy consumption and/or the energy saving gap [1, 33]. For example, from a previous study, we know that ventilation with heat recovery reduces energy more in dwellings that are well insulated and have a high airtightness than in those that are poorly insulated and have low airtightness [34]. This would mean that the energy efficiency state of the building prior to the thermal renovation influences the amount of energy saved. Regarding building type, we expect that insulation measures would be more profitable for single-family dwellings than for multifamily dwellings because the former generally have a relatively larger building envelope area. This means that heat loss because of poor insulation has a larger impact on single-family dwellings than on multifamily dwellings. The level of employment is assumed to be correlated with the occupancy time of a building. Previous research found strong correlations between the number of occupancy hours and residential energy consumption [35-37]. The number of household members was found to correlate with residential energy consumption [37-40]. Finally, income was also often mentioned as being influential on residential energy consumption [30, 41].

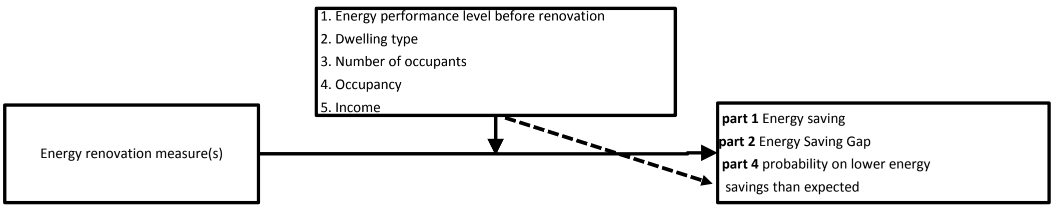

FIG. 3.2 Research method parts 1, 2 and 4 (dashed line are direct effects in part 4)

Because the rebound and prebound effect are expected by several researchers to be a main cause of lower energy savings than expected, we apply in the third part of this research descriptive statistics in which we define if the rebound and/or prebound effect occur. The prebound effect is assumed to occur if the energy consumption before renovation is more than 10% lower than expected. The rebound effect is assumed to occur if energy consumption after renovation is more than 10% higher than expected. And finally we conclude this paper with a logistic regression in which we investigate the influence of the above-mentioned occupant and building characteristics on the probability that thermal renovations result in lower-than-expected energy savings (Figure 3.2). Since we expect that the occupant and building characteristics do not only have a direct effect (continuous lines in Figure 3.2) on the probability of overestimated saving effects but also an interaction effect (dashed lines in Figure 3.2) we also add interaction terms of the building and occupant characteristics in the regression.

3.5 Description of thermal renovation in this paper

To prevent confusion and because the terms ‘maintenance’ and ‘renovation’ are often used interchangeably, this section defines what we (in this paper) understand by thermal renovations. We define in this paper thermal renovation as renovation measures that are taken to reduce energy consumption used for thermal comfort. We identify four different types of thermal renovations. The first is the single thermal renovation measure, which is defined as a significant improvement (going from at least one category to another (Table 3.1) of only one building component. The building components that are considered are: roof insulation, floor insulation, façade insulation, window improvements, heating system, domestic hot water system (dhw system) and ventilation system. If dhw system and heating system are replaced at the same time, then this is identified as one measure, because most buildings in the Netherlands use a combined heating and dhw system. The second type of thermal renovation is a significant improvement in the insulation level of the entire building envelope. This means that at least two components are significantly improved in terms of insulation. The third type of thermal renovation is a significant improvement in all building installations (heating, dhw and ventilation). The fourth type of thermal renovation is deep renovation, which refers to a significant improvement in at least three building components that bring them to a level equal to or higher than the current building regulation standards. To determine whether the improvement is significant, we categorised the thermal renovations. The change from one “higher” category (see Table 3.1 for categories) to another is assumed to be a significant

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improvement. Additionally, the improvements of the building installations must meet at least the current renovation standards (Table 3.1). For example, in this paper, the replacement of a boiler is only considered to be a thermal renovation if the new boiler has an efficiency of 0.95 (HR107 boiler). The categories are based on the Dutch ISSO publication 82.3 [29] (Table 3.1). We choose to use those categories because also the theoretical energy consumption is based on those. The change from natural ventilation to mechanical exhaust ventilation is also considered to be an improvement, despite the fact that this change is not per se expected to result in a theoretical energy reduction.

TABLE 3.1 Categories of building characteristics based on ISSO 82.1 2011

	Categories						
	Window (frame + glazing) [W/m2K]*	Floor insulation [Km²/W]	Façade insulation [Km²/W]	Roof insulation [Km²/W]	Heating system	dhw	Ventilation
1	Single glass (U≥4.2)	No-insulation (Rc≤ 0.32)	No-insulation (Rc≤ 0.36)	No-insulation (Rc≤ 0.39)	Local gas heater	Tankless gas water heater	Natural ventilation
2	Double glass(2.85≤ U<4.2)	Insulated cavity 32<Rc≤ 0.82	Insulated cavity 0.36<Rc≤ 0.86	Insulated cavity 0.39<Rc≤ 0.89	Conventional boiler (η<0.80)	Electric boiler	Mechanical exhaust ventilation
3	HR+ glass (1.95≤ U<2.85)	Up to40 mm insulation 0.82≤ 1.15	Up to40 mm insulation 0.86≤ 1.36	Up to40 mm insulation 0.89≤ 1.22	Improved non-condensing boiler (η=0.8-0.90)	Conventional combi boiler (η =0.80)	Demand based mechanical exhaust ventilation **
4	HR++ glass(1.75≤ U<1.95)	40- 80mm insulation 1.15<Rc≤ 2.15	40- 80mm insulation 1.36<Rc≤ 2.36	40-80mm insulation 1.22<Rc≤ 2.22	Condensing boiler (η=0.925-0.95)	Improved non-condensing combi boiler (η=0.80-0.9)	Balanced ventilation with heat recovery ***
5	Triple insulation glass (U<1.75)	80-120 mm insulation 2.15<Rc≤ 3.15	80-120 mm insulation 2.36<Rc≤ 3.36	80- 120 mm insulation 2.22<Rc≤ 3.22	Condensing boiler (η=0.90-0.925)	Condensing combi boiler (η=0.90-0.95)	
6		120-160 mm insulation 3.15<Rc≤ 4.15	120-160 mm insulation 3.36<Rc≤ 4.36	120-160 mm insulation 3.22<Rc≤ 4.22	Condensing boiler (η>0.95)		
7		160-200 mm insulation 4.15<Rc≤ 5.15	160-200 mm insulation 4.36<Rc≤ 5.36	160-200 mm insulation 4.22<Rc≤ 5.22			
8		More than 200mm insulatin Rc>5.15	More than 200mm insulatin Rc>5.36	More than 200mm insulatin Rc>5.22			

** Wooden/plastic window frames are assumed*

*** Mechanical exhaust ventilation, rate is determined by CO_2 level in the house*

**** Mechanical ventilation system (inlet and exhaust) that uses a heat recovery system to minimize heat loss due to ventilation*

The categorization of renovation measures makes that we can identify if a renovation took place. For this study we do not distinguish the different levels of renovation e.g. we don't take into account if a facade is renovated category 1 to 2 or from 1 to 5. Although this could also be an interesting topic for research in this study we assume that the renovation and the level of renovation is a choice that is taken carefully considering available budget on the moment of renovation, available techniques and practical aspects. The research of Majcen et al. [5] gives more insights on this topic.

3.6 Results

In this result section we start with an in depth analysis of the energy savings followed by in depth analysis of the energy saving gap and descriptive statistics of the rebound and prebound effect finally we conclude with a detailed logistic regression.

The descriptive statistics in Table 3.2 show the number renovated houses that resulted in higher savings than expected, lower savings than expected and savings that are almost similar to what was expected. The table also demonstrates that almost 90,000 dwellings underwent a renovation within the renovation categories mentioned in section 5 (single measures; insulation of entire building envelope; improvement of building installations and deep renovations). As written in the method section all energy savings are corrected for degree days to make them comparable with theoretical energy consumption. Table 3.2 shows that on average, 40% of the cases have higher energy savings than expected, while 57% have savings that were lower than expected and only 3% of the renovations have well predicted results (10% higher or lower than the expected savings). We choose for 10% because previous comparisons of actual and theoretical energy consumption have shown that a prediction within a 10% range is very good. Further Table 3.2 indicates that deep renovations most often result in lower energy savings than expected (81%). The same holds true for thermal renovations where two or more insulation measures are applied. In 35% of the cases the improvement of building installations results in higher than expected energy consumption. Regarding the single measures, we observe that the improvement in the combined heating and dhw system and in façade insulation most often result in lower-than-expected energy savings.

TABLE 3.2 Number of cases per thermal renovation type comparison number of over- under and well predicted cases

Renovation measures 2010-2014	Frequencies	Frequencies -overestimated energy savings[a]	Frequencies - well estimated energy savings[b]	Frequencies - underestimated energy savings[c]
Single renovation measures	**78583**	**43556(55%)**	**2466 (3%)**	**32561 (42%)**
Insulation roof	*5164*	*3129 (61%)*	*138 (3%)*	*1897 (37%)*
Insulation floor	*10095*	*4367 (43%)*	*125 (1%)*	*5603 (56%)*
Insulation facade	*6504*	*4067 (63%)*	*160 (3%)*	*2277 (35%)*
window	*10103*	*5293 (52%)*	*291 (3%)*	*4519 (45%)*
Heating system	*7864*	*3790 (48%)*	*217 (3%)*	*3857 (49%)*
dhw system	*1895*	*1021 (54%)*	*13 (1%)*	*861 (45%)*
Combi dhw & heating	*27431*	*17158 (63%)*	*1389 (5%)*	*8884 (32%)*
Ventilation system	*9527*	*4731 (50%)*	*133 (1%)*	*4663 (49%)*
Building insulation	**3552**	**2405 (68%)**	**102 (3%)**	**1045 (29%)**
Building installation	**3848**	**2342 (61%)**	**169 (4%)**	**1337 (35%)**
Deep renovations	**1530**	**1246 (81%)**	**76 (5%)**	**208 (14%)**
Total	87513	49549(57%)	2913 (3%)	35151(40%)

a Overestimated energy savings in this paper means the energy saving is at least 10% lower than expected.
b Well estimated energy savings in this paper means the energy savings are not more than 10% higher than expected and 10% lower than expected
c Underestimated energy savings in this paper means that the energy saving is at least 10% higher than expected.

3.6.1 Average actual savings per thermal renovation measure

Figure 3.3 shows the average gas consumption per renovation measure. The results of the Kruskal-Wallis test, comparing the savings per renovation type, demonstrate that the actual energy savings per renovation measures differ significantly from each other ($H(11)=3,526.84$, $p<0.05$), although the difference between non-renovation and especially domestic hot water (dhw) and ventilation are only small compared to no renovation measure.

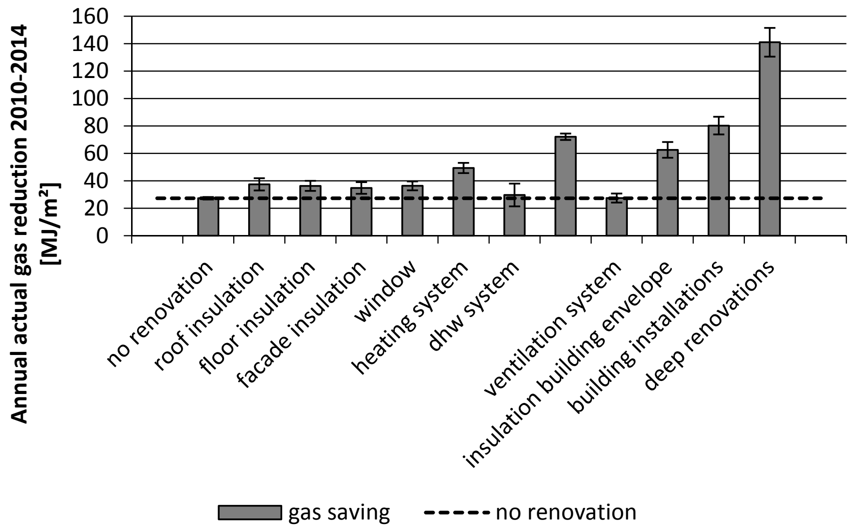

FIG. 3.3 Average energy saving (corrected for degree days) per thermal renovation measure (including confidence interval 0.05) dashed line is actual difference in gas reduction between 2010-2014 for non-renovated houses

Figure 3.3 demonstrates (as expected) that most gas is saved when deep renovations are executed. The results also indicate that the energy consumption of non-renovated dwellings also decreased. This phenomenon is also found in previous studies [5, 42] that used data from the same source. There are several reasons that explain why non-renovated dwellings have a decrease in heating consumption between the years 2010 and 2014, such as a change in occupant behaviour (perhaps occupants used lower thermostat settings, or they might have reduced the number of hours that heat their dwelling). Another explanation could be mistakes in the monitoring system; e.g. renovation measures not registered in SHAERE. We made the years comparable by correcting the energy consumption by degree days, although this is a common method the method has also drawbacks that possible cause the found energy saving of non-renovated houses [43]. Because the exact reason of this autonomous reduction is unclear we represented the energy reduction of non-renovated buildings with a dashed line in Figure 3.3 and the following figures. Taking this dashed line into account, Figure 3.3 suggests that an improvement of dhw system or ventilation system might not result in or only limited energy reduction. This could be true because the main aim of improving a dhw system or ventilation system is often to increase the comfort level and not to save energy. For ventilation

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this is especially the case in this dataset because most of the ventilation systems are renovated from a natural system to a mechanical exhaust system.

The average energy saving per renovation measures is known. However, we expect that occupant and building characteristics influence energy savings. We also expect that this influence is different per energy saving measure. Therefore, in the following paragraphs we compare the average saving per building and occupant characteristics per thermal renovation measure.

Average actual energy savings - energy efficiency of the building prior to thermal renovation

The Dutch government uses the energy index and the energy label to identify the energy efficiency of buildings. This index is based on the simplified heat loss calculation (see section 2), it is corrected for the floor area of the dwelling and the corresponding heat transmission areas [29]. The energy index is divided into several categories, which are the energy labels. Dwellings with an energy label A are supposed to be highly energy efficient, and dwellings with label G energy inefficient. In this section we investigate whether the energy label prior to the thermal renovation influences the average energy savings per renovation measure. Because almost no renovation measures are applied to dwellings with an energy label A, those dwellings are excluded from the analysis. The Kruskal Wallis test in Table 3.3 shows that we found significant differences between the average energy savings per energy label for all renovation measures. Roof insulation, facade insulation and deep renovations yield the expected results: Energy savings are higher for non-energy-efficient dwellings than for energy efficient-dwellings. For the renovation measures 'improvements of the windows', 'insulation of building envelope' and 'building installations' we observe the same results, with the exception of dwellings with an energy label F or G. However, the confidence interval for those dwellings with a F and G label is relatively large. For the change in heating system and ventilation system we notice the opposite effect: energy-efficient-dwellings benefit more from an improved heating system than non-energy-efficient dwellings. In general, we found a relatively large confidence interval for the average energy reduction of dwellings with an energy label G, which indicates that the energy savings vary highly per case. Improvements in the dhw and floor insulation do not seem to be dependent on the energy label of the dwelling prior to thermal renovation.

TABLE 3.3 Kruskal Wallis test: Energy label - saving

Renovation measure	Kruskal Wallis test
Roof	$H(5)=19.082, p<0.05$
Floor	$H(5)=18.717, p<0.05$
Façade	$H(5)=45.853, p<0.05$
Window	$H(5)=76.566, p<0.05$
Heating	$H(5)=55.054, p<0.05$
Dhw	$H(5)=28.242, p<0.05$
Combi dhw & heating	$H(5)=57.371, p<0.05$
Ventilation	$H(5)=34.820, p<0.05$
Insulation	$H(5)=122.957, p<0.05$
Installations	$H(5)=39.486, p<0.05$
Deep renovation	$H(5)= 39.990, p<0.05$

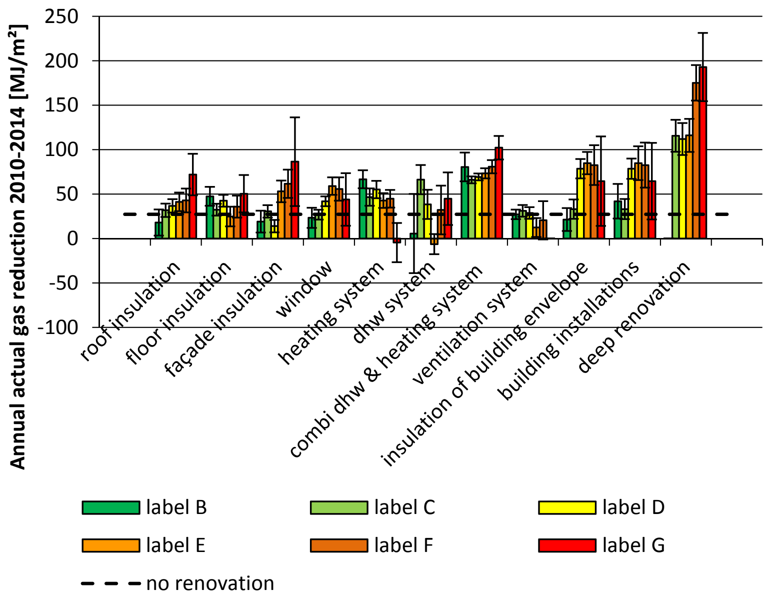

FIG. 3.4 Comparison between average energy saving (corrected for degree days) per renovation measure divided per energy label prior to thermal renovation and Kruskal Wallis test

As shown in Figure 3.4, roof, façade insulation, window improvements and insulation of the building envelope applied on dwellings with an energy label B (and sometimes also C) save less energy than dwellings that are not renovated (dashed line), which could mean that there is no significant energy saving. A possible explanation for this could be that dwellings with an energy label B are maybe not renovated, but administrative corrections are applied in the database. Because houses with a B label are already relatively efficient and therefore the probability that they will be renovated by the housing associations is lower. For two cases we found negative savings. The one for heating can be explained that in the Dutch case G label houses often have local gas heaters that have a lower capacity than newly installed heating installations which could lead to a higher consumption for heating because of increased comfort. Also for the improvement of domestic hot water system an increased comfort level could be an explanation for a negative energy savings.

Average actual energy savings - Type of dwelling

Apart from the energy efficiency of the dwelling prior to the renovation we also compared the influence of the type of dwelling on the effectiveness of an energy renovation (Figure 3.5). The results demonstrate that, on average, single-family dwellings always save more energy than multifamily dwellings (Figure 3.5). The figure also shows that the differences between multi and single family houses are almost similar for all renovation measures, which could indicate that there is no interaction effect between the renovation measures and the type of dwellings. Differently stated: a single family house benefits in terms of actual energy savings more from a thermal renovation than a multi-family house independently of which thermal renovation measure is taken. The only exception is the improvement of a dhw system and the change of all building installations, which could be explained by the fact that the use of dhw is not dependent on the building characteristics, such as the energy consumption for heating. Possible explanation why energy renovation measures are often more effective on single family houses than on multifamily houses is that single family houses have often compared to multifamily houses a relatively large building envelop that has a high influence of the energy use for heating.

TABLE 3.4 Man Withney U-test: Dwelling type - saving

Renovation measure	Man Withney U-test
Roof	Z(1)=2.036, p=0.154
Floor	Z(1)=1.316, p=0.251
Façade	Z(1)=8.092, p<0.05
Window	Z(1)=16.514, p<0.05
Heating	Z(1)=66.867, p<0.05
Dhw	Z(1)=2.148, p=0.143
Combi dhw & heating	Z(1)=68.555, p<0.05
Ventilation	Z(1)=18.997, p<0.05
Insulation	Z(1)=15.770, p<0.05
Installations	Z(1)=35.808, p<0.05
Deep renovation	Z(1)=2.036, p=0.154

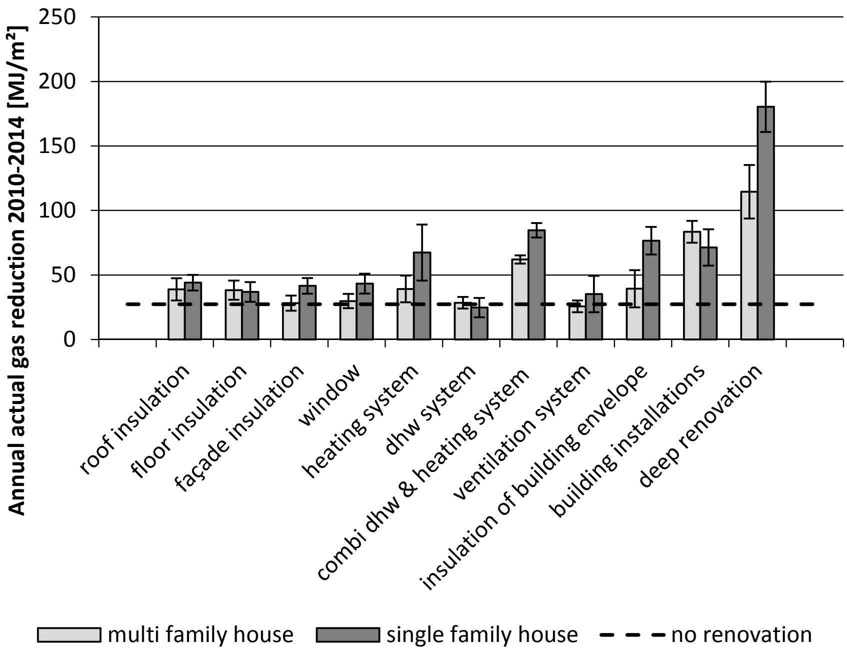

FIG. 3.5 Difference in actual energy saving (corrected for degree days) for single and multi-family dwellings and Man Withney U-test

Average actual energy saving -occupancy

The third comparison compares occupancy time of a house and the actual energy saving effect per measure. Previous studies demonstrated that occupancy has a highly significant influence on residential energy consumption [33,36,37,37,44]. Since occupancy data was not available, we assumed that households with one unemployed adult member have a higher occupancy time than households in which all adults have jobs. As shown in

Figure 3.6, renovation measures that improve building installations (heating, dhw system, ventilation, and all building installations) are all found to differ significantly for the group in which all (adult) household members work, compared to the group where at least one household member does not work. No significant differences are found for the other renovation measures. A possible explanation for the energy savings being influenced if the building installations are improved but not when the insulation level is improved could be that employed occupants have a more predictive occupancy pattern; therefore, the automatic control systems (for example, automatic thermostats) that often come with new building installations function better. However, this does not explain why the savings from hot tap water differ significantly. More research is needed to explain this phenomenon.

TABLE 3.5 Man Withney U-test: Employment - saving

Renovation measure	Man Withney U-test
Roof	Z(1)=11.782, p<0.05
Floor	Z(1)=2.110, p=0.146
Façade	Z(1)=0.009, p=0.923
Window	Z(1)=0.332, p=0.564
Heating	Z(1)=26.307, p<0.05
Dhw	Z(1)=24.686, p<0.05
Combi dhw & heating	Z(1)=6.952, p<0.05
Ventilation	Z(1)=28.042, p<0.05
Insulation	Z(1)=2.434, p=0.119
Installations	Z(1)=10.062, p<0.05
Deep renovation	Z(1)=0.451, p=0.502

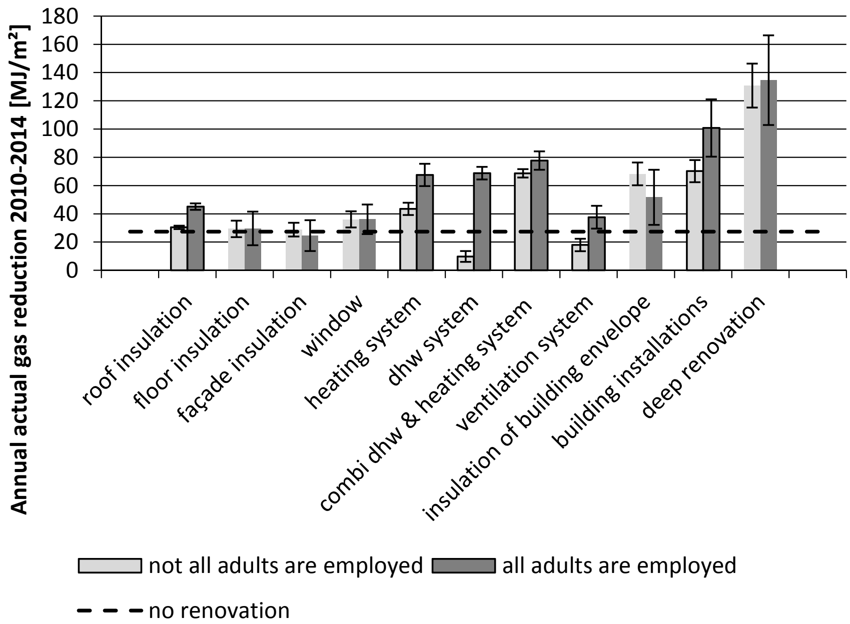

FIG. 3.6 Difference in energy saving (corrected for degree days) for households where all occupants have jobs and those in which not all occupants have jobs insignificant measures are shown transparent and Man Withney U-test

Average actual energy saving -income

The fourth comparison we make for energy saving is if energy savings per thermal renovation measure differ for incomes above versus below modal income. Based on previous literature, we would expect the average energy savings to be higher for people with a high income level than for those with a low income level [13, 45]. Figure 3.7 shows that for all significant cases, occupants with a salary above the modal income save more energy than occupants below the modal income. These results could confirm previous findings that occupants are more willing to compromise on comfort to save energy and money if they have a relatively low income. After the renovation, they need less energy to achieve the same comfort level; therefore, they can afford a higher comfort level, which results in lower energy savings.

TABLE 3.6 Man Withney U-test: Income - saving

Renovation measure	Man Withney U-test
Roof	Z(1)=5.246, p<0.05
Floor	Z(1)=13.466, p<0.05
Façade	Z(1)=5.265, p<0.05
Window	Z(1)=0.640, p=0.424
Heating	Z(1)=2.699, p=0.100
Dhw	Z(1)=5.506, p<0.05
Combi dhw & heating	Z(1)=7.198, p<0.05
Ventilation	Z(1)=6.781, p<0.05
Insulation	Z(1)=0.118, p=0.731
Installations	Z(1)=5.640, p<0.05
Deep renovation	Z(1)=1.380, p=0.240

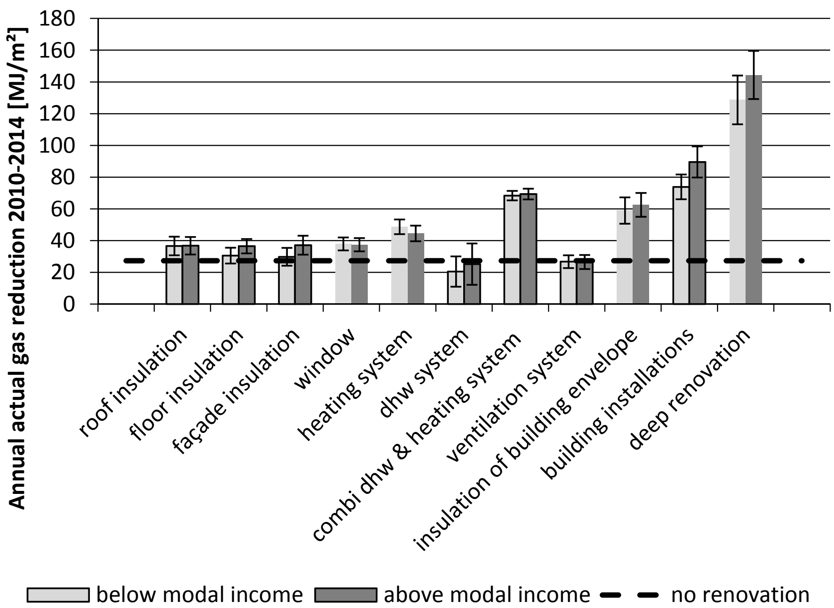

FIG. 3.7 Difference in energy saving (corrected for degree days) for households with below average incomes and those with above average incomes (insignificant measures are shown transparent) and Man Withney U-test

We also tested the influence of number of occupant but because we didn't find significant results we don't present them in the result section.

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3.6.2 Average energy saving gap per thermal renovation measure

For the energy saving gap (expected saving minus actual saving) we executed similar analysis as we did for the actual energy saving. The aim of these analyses is to obtain a better insight into the aspects that are important for energy saving predictions. The results should give us some guidance for aspect that should be improved in the Dutch energy calculation method. In Figure 3.8 we compare the ESG per renovation measure. The Kruskal-Wallis test confirms that all renovation measures differ significantly ($H(11)=11071.498$, $p<0.05$) compared to no renovation measures. Figure 3.8 demonstrates that eight of the eleven renovation measures demonstrate a positive energy saving gap, meaning that the expected energy saving was higher than saved in reality. A negative energy saving gap implies that in reality, more energy is saved than expected. This means that floor insulation and improvements in the heating and ventilation system save more energy than expected, while the other measures save less energy than expected. However also when no renovation measures are applied we see a negative ESG (Figure 3.8). If we take this into account all measures except floor insulation result in lower energy savings than expected.

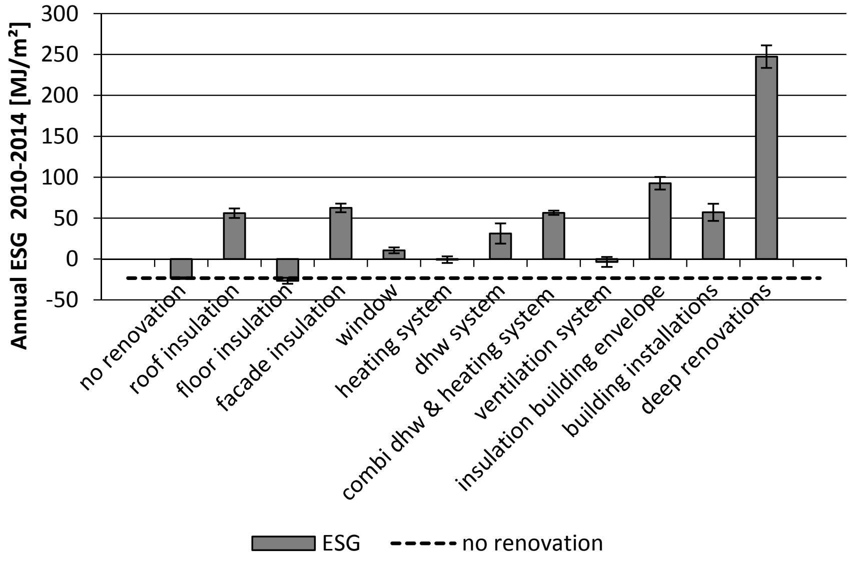

FIG. 3.8 Average energy saving gap per thermal renovation measure

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Average energy saving gap - Energy efficiency of the building prior to thermal renovation

Figure 3.9 demonstrate that the ESG of all types differs significantly depending on the energy efficiency status of the building before renovation. The results show that for all types of thermal renovations the energy saving gap is larger if the energy label is lower. Which means that renovations of houses with a low energy efficiency before renovation result in a bigger gap between estimated and actual energy saving. Only a change in the dhw system and floor insulation show different patterns. For dhw this is as expected because energy consumption for dhw is more related to occupant behaviour than to building characteristics.

TABLE 3.7 Kruskal Wallis test Energy label - ESG

Renovation measure	Kruskal Wallis test
Roof	H(5)=622.256, p<0.05
Floor	H(5)=20.115, p<0.05
Façade	H(5)=669.096, p<0.05
Window	H(5)=190.020, p<0.05
Heating	H(5)=297.538, p<0.05
Dhw	H(5)=434.609, p<0.05
Combi dhw & heating	H(5)=902.413, p<0.05
Ventilation	H(5)=97.024, p<0.05
Insulation	H(5)=1034.098, p<0.05
Installations	H(5)=148.644, p<0.05
Deep renovation	H(5)= 266.631, p<0.05

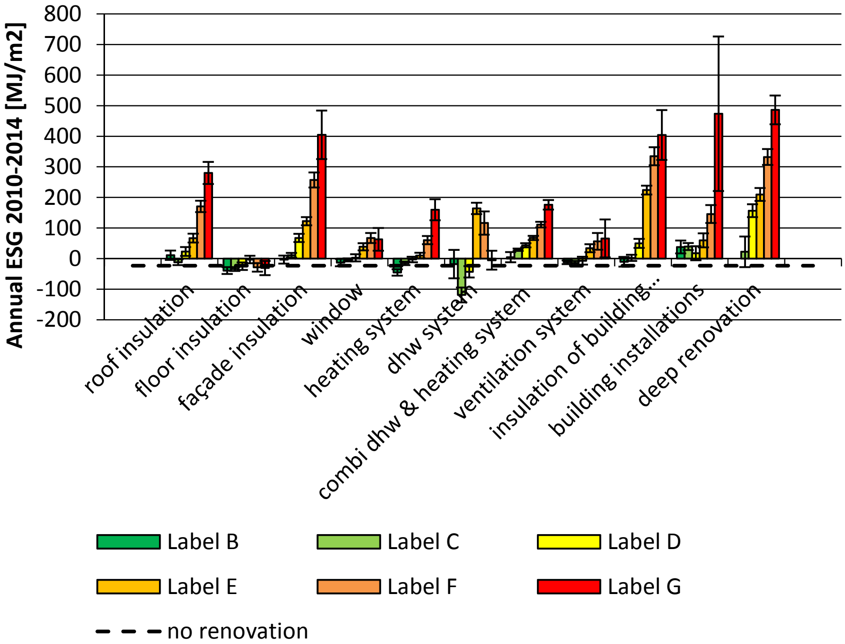

FIG. 3.9 Average energy saving gap per energy label of the building prior to renovation for every type of thermal renovation. and Kruskal Wallis test

Average energy saving gap - type of dwelling

With regard to the type of dwelling, the average energy saving gap differs significantly for floor, façade insulation, improvements in heating, dhw and ventilation systems, the insulation of the entire building envelope, the improvements in all building installation systems and the deep renovations (Figure 3.10).
The results show that the ESG is different per renovation measure. For most significant renovation measures we found a positive ESG (energy saving results are overestimated) with an exception for the ventilation system and single family houses with an improved dhw system. However for ventilation the ESG is smaller than the ESG for non-renovated houses. A renovation of the dhw system in single family houses shows a bigger negative ESG than the houses that are not renovated, this implies that on average a change of the dhw system in single family houses result on in more energy savings than expected.

TABLE 3.8 Man-Withney U-test: dwelling type - ESG

Renovation measure	Man Withney U-test
Roof	Z(1)=14.435, p<0.05
Floor	Z(1)=0.604, p=0.437
Façade	Z(1)=63.121, p<0.05
Window	Z(1)=0.006, p=0.937
Heating	Z(1)=20.219, p=0.100
Dhw	Z(1)=56.751, p<0.05
Combi dhw & heating	Z(1)=7.344, p<0.05
Ventilation	Z(1)=4.692, p<0.05
Insulation	Z(1)=57.014, p<0.05
Installations	Z(1)=5.555, p<0.05
Deep renovation	Z(1)=16.820, p<0.05

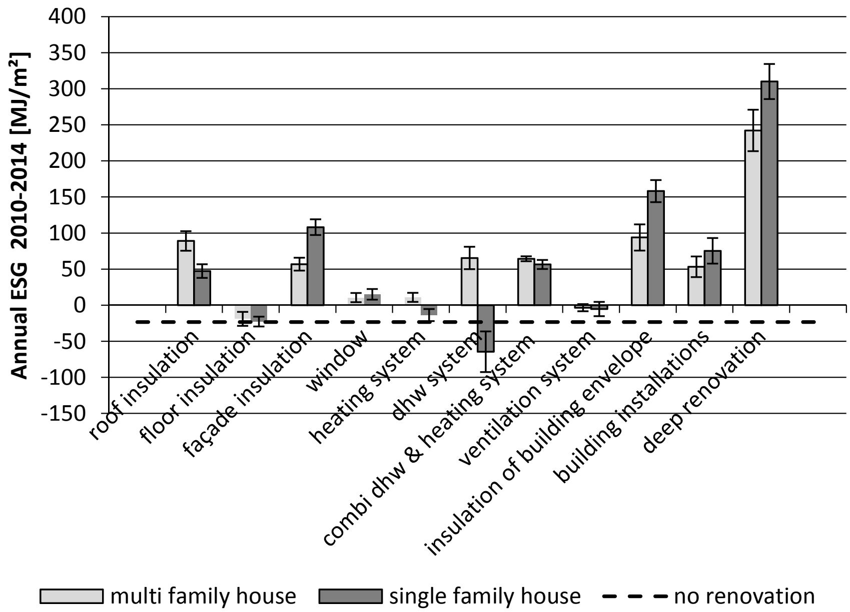

FIG. 3.10 Average energy saving gap, multifamily dwelling and single family dwellings compared per thermal renovation measure. Insignificant measures are shown transparent

Average energy saving gap - Occupancy

Figure 3.11 illustrates that there are only a few types of renovation that show a significant differences in ESG between houses where all adults work and houses where not all adults work. Most of those measures are building installations measures (heating system; dhw system; combi dhw & heating system and ventilation system). We have seen a similar effect in the actual energy savings (section 5.2.3). The only exception is insulation of the building envelope, but although significant the differences for that measure are relatively small.

TABLE 3.9 Results Man-Withney U-test: ESG - (un)employed

Renovation measure	Man Withney U-test
Roof	Z(1)=-1.893, p=0.058
Floor	Z(1)=-0.687, p=0.492
Façade	Z(1)=-1.464, p=0.143
Window	Z(1)=-1.751, p=0.080
Heating	Z(1)=-5.012, p<0.05
Dhw	Z(1)=-10.151, p<0.05
Combi dhw & heating	Z(1)=-2.111, p<0.05
Ventilation	Z(1)=-2.432, p<0.05
Insulation	Z(1)=-1.977, p<0.05
Installations	Z(1)=-0.330, p=0.741
Deep renovation	Z(1)=-0.323, p=0.746

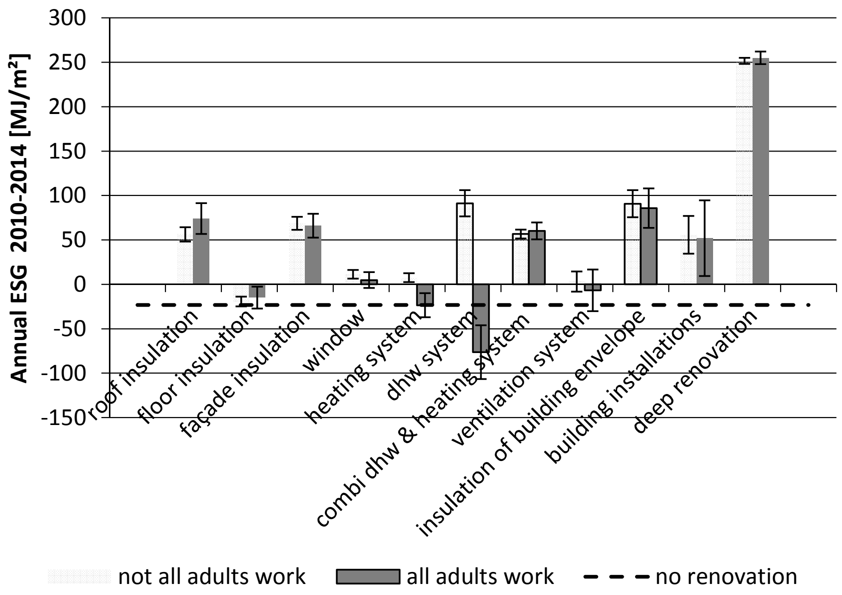

FIG. 3.11 Average energy saving gap, households in which not all adults work and those where all adults work are compared per thermal renovation measures. Insignificant measures are shown transparent

Average energy saving gap - income

A comparison of occupants' earnings below and above the national modal income reveals significant differences for the average energy saving gap of floor insulation, façade insulation, heating, ventilation and the insulation of the building envelope. In the cases with overestimated energy savings (positive energy saving gap), we notice that the households with an income below the national modal is larger than those with a higher income (Figure 3.12), whereas the opposite holds true for the measures with a negative energy saving gap. This could indicate people with a low income living in energy-inefficient dwellings are more willing to reduce their comfort levels to save money than households with a high income.

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TABLE 3.10 Results Man Withney U-test: ESG - income

Renovation measure	Man Withney U-test
Roof	Z(1)=-0.190, p=0.850
Floor	Z(1)=-3.825, p=<0.05
Façade	Z(1)=-2.599, p<0.05
Window	Z(1)=-1.152, p=0.249
Heating	Z(1)=-2.679, p<0.05
Dhw	Z(1)=-7.228, p<0.05
Combi dhw & heating	Z(1)=-1.188, p=0.235
Ventilation	Z(1)=-0.330, p=0.741
Insulation	Z(1)=-3.134, p<0.05
Installations	Z(1)=-0.671, p=0.502
Deep renovation	Z(1)=-0.686, p=0.493

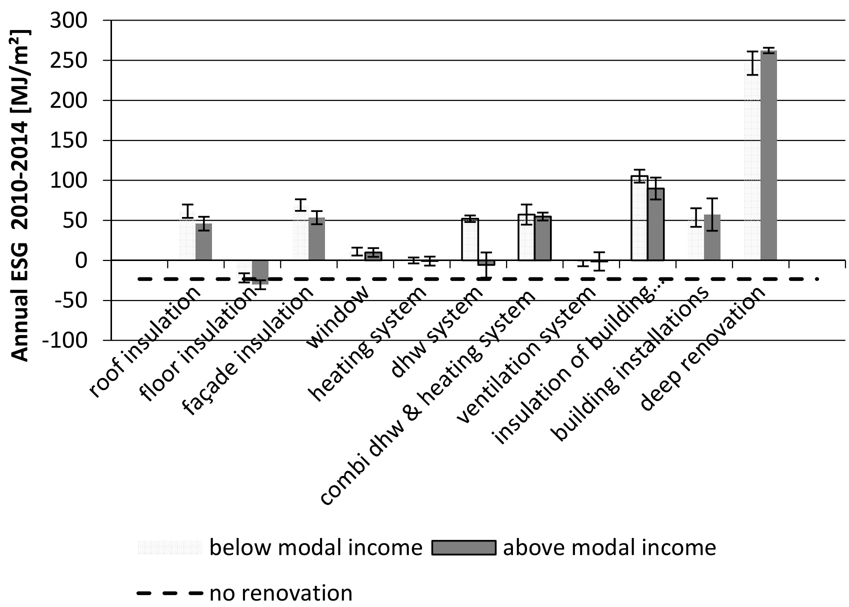

FIG. 3.12 Average energy saving gap, households with an income below and above the national average are compared per thermal renovation measures. Insignificant measures are shown transparent

3.6.3 Occurrence of the prebound and rebound effect

Since previous studies assume that the rebound and prebound effects are the most important explanations for lower energy saving effects than expected, we take a closer look at those effects in this section. If the prebound and rebound effects are indeed the main cause of the energy performance gap, we would expect that the energy consumption before renovation is often lower than expected and the energy consumption after renovation is often higher than expected. If only the prebound effect occurs, we expect a lower energy consumption than expected before a thermal renovation and an energy consumption as expected after renovation. If only the rebound effect occurs, we would expect energy consumption as estimated before renovation and a lower energy consumption as expected after thermal renovations. In Table 3.11 we determined the number of buildings that have a higher, lower or similar as expected energy consumption. The table shows that both the rebound and/or prebound effects occurred only for a limited number of cases. Most households maintain their 'habit' by using more energy than expected before and after renovation or using less energy than expected before and after renovation. If we check per thermal renovation measure, we observe more or less the same 'pattern' for most renovation measures as listed in Table 3.11. However, for deep renovations, we note that the prebound and rebound effects together occur significantly more often (30%) than for the other renovation measures. This indicates that while those effects are responsible for some of the overestimated energy savings, they are not the only reason.

TABLE 3.11 Frequencies of over- and underpredicted energy consumption prior to and post thermal renovation

		After renovation		
		Underprediction	Well predicted	Overprediction
Before renovation	Underprediction	16538 (20%)	**3598 (4%)**[b]	3904 (5%)
	Well predicted	5639 (7%)	4576 (6%)	**5339 (6%)**[c]
	Overprediction	**6049 (7%)**[a]	6498 (8%)	31749 (38%)

a prebound & rebound effect / b prebound effect / c rebound effect

3.6.4 Probability of lower energy savings than expected

Because the previous section indicated that the rebound and prebound effect are not the only cause of lower energy savings than expected, we conduct a binary logistic regression analysis to identify which other parameters influence the probability on lower energy savings than expected. As mentioned before we consider the energy saving results to be lower than expected if the saving is more than 10% lower than calculated. The independent variables used in the logistic regression are the building and occupant characteristics that we discussed earlier as well as the energy saving measures and the energy performance gap of the building before the thermal renovation (Table 3.12). This parameter is added because previous studies state that next to the prebound and rebound effects, a probable explanation for the energy saving gap are an incorrect assumption in the energy calculation before renovation [1, 17]. As a second step of the logistic regression, we include the interaction between the thermal renovation type and the building and occupant characteristics because the previous sections demonstrated that these characteristics influence the energy savings differently per type of thermal renovation.

TABLE 3.12 Variables in logistic regression (DV=dependent variable, IV=Independent variable)

Type of variable	Variable	Categories
DV	Lower energy savings than expected	Yes/no (1/0)
IV	Thermal renovations	No renovation, Roof*, floor, façade, window, heating, dhw, combi dhw & heating, insulation, installations, deep renovation
IV	Energy index	Continuous variable
IV	Building type	Single family dwellings*/ multi family dwellings
IV	Occupancy	All adults work/at least one adult does not work
IV	Income	Above national middle income/below national middle income
	Energy performance Gap	The energy saving gap prior to the thermal renovation (Energy performance gap <0, actual energy consumption lower than estimated, energy performance gap>0 actual energy consumption higher than estimated)
IV	Interaction	All building and occupant characteristics variables * thermal renovation measures
IV	Interactions	Energy performance gap of year 2010 · Energy index

The binary logistic regression without interaction effects, demonstrates an insignificant result for the energy efficiency state of the building prior to thermal renovation, dwelling type and income. This is unexpected, since the previous analysis suggested that there is a relation between those parameters and the effectiveness of a renovation measure. We will examine the influence of the energy efficiency of a building when we look at the interaction effects. Most of the thermal renovation measures demonstrate a significant effect. A change in the dhw system increases the chance on lower savings than expected the most (odds ratio of 3.799). The occupancy level based on all occupants working or at least one adult occupant not working demonstrates that a low occupancy results in lower energy saving effects than expected more often than a high occupancy level. Finally, a large energy performance gap (which means the expected energy consumption is higher than the actual energy consumption) in the year 2010, when thermal renovations are not yet applied, result in higher chances that the energy saving results would be overestimated.

TABLE 3.13 Logistic regression results without interaction effects (Odds ratio above 1 higher chance on lower energy savings than expected, Odds ratio below 1 lower chance on lower energy savings than expected)

		95% CI for Odds Ratio		
	B(SE)	Lower	Odds ratio	upper
Energy Index	-0.047(0.28)	0.902	0.954	1.008
Renovation measures*	**			
Floor insulation	-0.352 (0.067)**	0.617	0.703	0.802
Façade insulation	0.095 (0.071)	0.958	1.100	1.263
Window	-0.350(0.062)**	0.621	0.705	0.800
Heating system	-0.573(0.065)**	0.496	0.564	0.640
dhw system	1.251(0.110)**	2.814	3.493	4.335
Combi dhw & heating system	-0.276(0.059)**	0.676	0.759	0.851
Ventilation	-0.353(0.065)**	0.619	0.702	0.797
Insulation	0.139(0.093)	0.959	1.150	1.378
Installations	0.098(0.076)	0.951	1.103	1.279
Deep renovations	0.588(0.138)**	1.374	1.801	2.359
Single family dwelling*	0.022(0.029)	0.676	0.759	1.036
Income *	-0.046(0.028)	0.924	0.978	1.105
Occupancy*	-0.182(0.028)**	0.991	1.047	0.880
Energy Performance Gap	0.073(0.002)**	0.790	1.076	1.080
Constant	0.865(0.076)**		2.375	

*** Result is significant $p<0.05$, R^2=0.064 (Cox&Snell) 0.089 (Nagelkerke). Model $\chi2(15)=2754.971$, $p<0.05$.*

The first binary logistic regression is followed up with a second logistic regression using interaction effects. The interactions are based on the results we found in the previous sections. Based on the increase of the Cox and Snell R^2 and the Nagelkerke R^2, we can conclude that some of the interactions that we found in the previous sections are indeed present, and they contributed significantly to predicting the probability of energy saving effects after renovations will be lower than expected (Table 3.14). The interactions between "income and renovations" and "occupancy and renovations" are insignificant; therefore, they are not included in the model. For the energy efficiency of the building prior to the renovation we only found interactions effects and no direct effects. For those interactions we found significant effects for most renovation measures. Most building installation renovation measures show a higher chance on lower than expected energy savings after renovation when the building has a high energy efficiency, while the opposite applies for the insulation measures. Except for floor insulation and improved windows, the chance on lower than expected savings increases for those measures when the energy efficiency of the house increases. This confirms the findings in Figure 3.4 and Figure 3.9. Only for renovation measure "heating system" we found unexpected results, those show that the chance on lower than expected savings is higher for buildings with a high energy efficiency. Almost all renovation measures, except the change in ventilation system, dhw system and deep renovations demonstrate significant interaction effects with the type of building (Table 3.14). The interaction per building type indicate that the probability of lower than expected energy saving are more likely for multi-family dwellings. Only if the dhw system, heating system or all building installations are replaced the probability on lower than expected energy savings is more likely for single family houses, however those parameters are found to be insignificant. Those results confirm the findings shown in Figure 3.5 and Figure 3.10. We didn't find significant interaction effects for income and occupancy and they are therefore not included in the final regression table results (Table 3.14).

TABLE 3.14 Logistic regression results with interaction effects (Odds ratio above 1 higher chance on lower energy savings than expected, Odds ratio below 1 lower chance on lower energy savings than expected)

	95% CI for Odds Ratio			
	B(SE)	Lower	Odds ratio	upper
Renovation measures*/**				
Floor insulation	0.822 (0.174)**	1.1618	2.275	3.200
Façade insulation	-0.931(0.239)	0.0247	0.394	0.629
Window	0.056(0.164)	0.767	1.058	1.458
Heating system	-1.477(0.157)**	0.168	0.228	0.310
dhw system	1.276(0.488)**	1.489	3.584	8.627
Combi dhw & heating system	-0.220(0.112)	0.645	0.803	1.000
Ventilation	-0.367(0.154)**	0.512	0.693	0.937
Insulation	-1.359 (0.353)**	0.129	0.257	0.513
Installations	0.559 (0.239)	1.094	1.749	2.796
Deep renovations	-1.012 (0.646)	0.102	0.363	1.289
Single family dwelling*	-0.335(0.110)**	0.576	0.715	0.887
Occupancy*	-0.175(0.028)**	0.808	0.851	0.896
Energy Performance Gap	0.076(0.002)**	1.075	1.079	1.083
EI*ren. Measure**				
EI * floor insulation	-0.760(0.080)**	0.400	0.468	0.547
EI * façade insulation	0.539(0.142)	1.298	1.715	2.264
EI*window	-0.329(0.080)**	0.615	0.720	0.842
EI * heating	0.506(0.077)**	1.426	1.658	1.927
EI*dhw	-0.022(0.224)	0.630	0.978	1.518
EI*combi dhw & heating	-0.122(0.043)**	0.813	0.885	0.964
EI * ventilation	-0.070(0.086)	0.789	0.933	1.103
EI * insulation	0.681(0.206)**	1.319	1.976	2.959
EI * installations	-0.317(0.123)**	0.573	0.729	0.927
EI*deep renovations	0.578(0.331)	0.967	1.782	3.283

>>>

TABLE 3.14 Logistic regression results with interaction effects (Odds ratio above 1 higher chance on lower energy savings than expected, Odds ratio below 1 lower chance on lower energy savings than expected)

Renovation measure* building type**				
Single family*floor insulation	0.421(0.134)**	1.172	1.524	1.981
Single family * façade insulation	0.362(0.152) **	1.067	1.436	1.932
Single family * window	0.387(0.133) **	1.135	1.472	1.909
Single family * heating	-0.208(0.140)	0.617	0.812	1.068
Single family * dhw	-0.971 (0.299) **	0.211	0.379	0.680
Single family * combi dhw & heating	0.442(0.124) **	1.220	1.557	1.986
Single family * ventilation	0.238(0.143)	0.960	1.269	1.678
Single family * insulation	0.734(0.194) **	1.425	2.082	3.043
Single family * installations	-0.034 (0.186)	0.671	0.967	1.394
Single family * deep renovation	1.052 (0.324) **	1.519	2.863	5.398
Constant	0.922(0.079)**		2.514	

*** Result is significant $p<0.05$, $R2=0.081$ (Cox&Snell) 0.112 (Nagelkerke). Model $\chi2(45)=3094.123$, $p<0.05$*

3.7 Discussion

Regarding the data used in this paper one of the strengths is that a relatively large dataset containing pre- and post-renovation energy consumption data was used. Despite this large database, the data, especially of the occupants and energy consumption, were only available on an aggregated level. Therefore, there could be other parameters that influence the energy saving effects that are not taken into account in this analysis. Further research on the influence of other parameters is required to indicate whether they also play a role. Another disadvantages of the data used in this paper is that the data is only from social housing in the Netherlands; therefore, the dwellings are all rental dwellings. This means that the occupants did not initiate the renovations themselves, which might have had significant effects on the results, because previous studies demonstrated that, in some cases, tenants behave differently than home owners [11, 46]. Furthermore the occupants living in social housing in the Netherlands have on average a lower income than the average income of the Netherlands. However, since the Dutch social housing sector is relatively large (30% of the total housing stock) compared to other countries, the dataset also contained a significant number of households with an income above the national average. Therefore the results can be considered representative. Another aspect that we should take in consideration when interpreting the results of the ESG analysis and the logistic regression is that the theoretical energy consumption used in this paper is based on a quasi-steady state calculation method, although several studies mention that using a steady state calculation method is acceptable for prediction year-round energy needs [47].

Regarding the methods used in this paper, one of the strengths, in comparison to previous studies, is that both the occupant and the building characteristics are taken into account, and only dwellings with the same occupants before and after renovations were considered in the analysis. Another, strength of this paper is that we investigated both actual savings and the energy saving gap, therefore a better insight was not only provided in the actual effect of thermal renovation, but also into the aspects that need attention/improvements in the energy calculation method. To identify if a renovation measure was applied we used categories, we assumed a renovation measure was executed if the building characteristics belonged to a “better” category in the year 2014 than in 2010. One advantage of this method is that we avoid minimal changes in the database that do not contribute to a better performance, however we might also have lost some cases that fell on the edges of the categories. For this study we assume that the renovation and the level of renovation is a choice that is taken carefully considering available budget on the moment of renovation, available techniques and practical aspects. Therefore we do not distinguish the different levels of renovation (e.g. how much a building is extra insulated).

The results demonstrate that there is a significant energy reduction when no renovation measures are taken. A possible explanation could be the change in behaviour. However, another (probably more likely) explanation is errors in the monitoring process. Social housing companies in the Netherlands must update their data every year, but since this is a manual process done by many different people, errors can easily be made. Further we used a correction for degree days however this method also has drawbacks as mentioned in Azevedo et al. [43]. Despite its limitations, this research provides new insights and confirms existing theories about the reasons energy saving renovations often result in lower-than-expected energy savings.

3.8 Conclusion

The aim of this study was to get a better insight in the real energy savings after thermal renovations and in the reasons why they often result in lower energy savings than expected. Based on this research, we can conclude that the amount of energy saved after a thermal renovation is dependent on the energy efficiency of the dwelling prior to the thermal renovation, type of dwelling, income level of household and occupancy. However, the number of occupants per house was not found to have a significant effect. From the investigated types of renovation measures, deep thermal renovations have on average the highest energy saving gap (250MJ), despite this deep renovations save on average (141MJ) still the most energy. Apart from deep renovations it is impossible to conclude which thermal renovation measure is the most effective because the results show that it is dependent on indirect and direct aspects. This means that because every situation is unique, tailored thermal renovation advice is needed to decide on the most effective thermal renovation measure. Relatively energy efficient dwellings prior to a thermal renovation benefit on average more from improvements of the building installations, while dwellings that are energy inefficient prior to the thermal renovations benefit on average more from an improved building envelope. Energy savings due to thermal renovations are on average higher for single-family dwellings than for multifamily dwellings, with the exception of dhw systems. We also found indications that a high occupancy time seems to have a negative effect on the energy savings when new building installations are installed. Better instructions regarding these installations after they are fitted might be a solution to increase the energy saving effect of these renovation measures. Furthermore, we indicate that occupants with a high income save on average more energy than occupants with low income. Based on these results, one should consider that while the thermal renovations for a household with a low income might be lower than expected, they will increase comfort.

For the energy saving gap, we found like in previous studies that the energy savings for low energy efficient buildings prior to thermal renovations are not well predicted. It is important that more research is conducted to improve the assumptions we make for these buildings in order to reduce the energy saving gap and prevent lower than expected saving effects and payback times. The results also indicate that this is probably even more important for single-family dwellings than for multifamily dwellings. Furthermore, we found that maybe more attention should be paid to building installations and how occupants use them because we observe that the energy saving gap is significantly larger if occupants are more often at home and the building installations are changed.

The analysis of the occurrence of the energy performance gap before and after renovation showed that only in 7.6% of the cases a prebound and rebound effect occurred. This percentage is different per renovation measure. As expected, the prebound and rebound effect occur significantly more often in buildings that underwent a deep renovation than in buildings that underwent a single measure renovation. However, the results also show that if the occupant consumes more energy than expected before the thermal renovation, they often also consume more energy than expected after renovation and the other way around. This means that the rebound and prebound effect explain only part of the energy saving gap.

The logistic regression showed that the energy efficiency prior to the renovation, type of dwelling and occupancy have a significant effect on the probability that energy savings after thermal renovations result in lower energy savings than expected, we did not only find direct effects but also interaction effects. The influence of the energy efficiency of the building prior to the thermal renovation and the type of dwelling is dependent on the type of thermal renovation that is applied.

Overall, this paper has shown new insights towards the influence of the energy efficiency state of a building prior to thermal renovation, the type of building, the number of occupants, the income level of the occupants and the occupancy time on the actual energy savings, the energy saving gap and on the probability on lower energy savings than expected. For more accurate estimations towards energy savings after renovations, those influencing factors should be taken into account as direct and indirect (interaction) effects. The results could also be used to have more realistic expectations of the energy reduction achieved by thermal renovations, which is important for (amongst others) policymakers, clients and contractors who make use of energy performance contracting, home owners, landlords and (social) housing associations. Although this paper showed the most effective thermal renovation measures for specific household and building characteristics, the costs of the renovation measures should also be taken into account to make a realistic assessment which measure is the best to apply for a specific case. Therefore, we advise that further research towards effective thermal renovations should include the costs and benefits of the different renovation types.

References

[1] Majcen, D., L. Itard, and H. Visscher, Actual and theoretical gas consumption in Dutch dwellings: What causes the differences? Energy Policy, 2013. **61**: p. 460-471.

[2] Guerra Santin, O., Actual energy consumption in dwellings; the effect of energy performance regulations and occupant behaviour. OTB, ed. S.U. Areas. 2010, Delft: TU Delft. 237.

[3] Delghust, M., Y. De Weerdt, and A. Janssens, Zoning and Intermittency Simplifications in Quasi-steady State Models. Energy Procedia, 2015. **78**: p. 2995-3000.

[4] Sunikka-Blank, M. and R. Galvin, Introducing the prebound effect: the gap between performance and actual energy consumption. Building Research & Information, 2012. **40**(3): p. 260-273.

[5] Majcen, D., L. Itard, and H. Visscher, Actual heating energy savings in thermally renovated Dutch dwellings. Energy Policy, 2016. **97**(Supplement C): p. 82-92.

[6] Filippidou, F., N. Nieboer, and H. Visscher, Effectiveness of energy renovations: a reassessment based on actual consumption savings. Energy Efficiency, 2018.

[7] Raynoud, M., et al., An energy efficiency program analysis to understand the gaps between ex-ante and ex-post evaluations, in 2012 International Energy Program Evaluation Conference. 2012.

[8] Galvin, R., Making the 'rebound effect' more useful for performance evaluation of thermal retrofits of existing homes: Defining the 'energy savings deficit' and the 'energy performance gap'. Energy and Buildings, 2014. **69**: p. 515-524.

[9] Haas, R. and P. Biermayr, The rebound effect for space heating Empirical evidence from Austria. Energy Policy, 2000. **28**(6–7): p. 403-410.

[10] Gram-Hanssen, K., Efficient technologies or user behaviour, which is the more important when reducing households' energy consumption? Energy efficiency, 2012. **6**: p. 447-457.

[11] Aydin, E., N. Kok, and D. Brounen The rebound effect in residential heating. 2013. 33.

[12] Gram-Hanssen, K., Retrofitting owner-occupied housing: remember the people. Building Research & Information, 2014. **42**(4): p. 393-397.

[13] Sorrell, S., J. Dimitropoulos, and M. Sommerville, Empirical estimates of the direct rebound effect: A review. Energy Policy, 2009. **37**(4): p. 1356-1371.

[14] Ferreira, M. and M. Almeida, Benefits from Energy Related Building Renovation Beyond Costs, Energy and Emissions. Energy Procedia, 2015. **78**: p. 2397-2402.

[15] Roberti, F., et al., Energy retrofit and conservation of a historic building using multi-objective optimization and an analytic hierarchy process. Energy and Buildings, 2017. **138**: p. 1-10.

[16] Visscher, H., J. Laubscher, and E. Chan, Building governance and climate change: roles for regulation and related polices. Building Research & Information, 2016. **44**(5-6): p. 461-467.

[17] Rasooli, A., L. Itard, and C.I. Ferreira, A response factor-based method for the rapid in-situ determination of wall's thermal resistance in existing buildings. energy and buildings, 2016. **119**: p. 51-61.

[18] Majcen, D., Predicting energy consumption and savings in the housing stock - A performance gap analysis in the Netherlands, in Architecture and the Built Environment. 2016, Delft University of Technology: Delft. p. 224.

[19] Lucchi, E., Applications of the infrared thermography in the energy audit of buildings: A review. Renewable and Sustainable Energy Reviews, 2018. **82**: p. 3077-3090.

[20] Laurent, M.H., et al., Back to reality: How domestic energy efficiency policies in four European countries can be improved by using empirical data instead of normative calculation, in ECEEE 2013 Summer Study - Rethink, Renew, Restart. 2013, ECEEE: France. p. 2057-2070.

[21] BPIE, Renovation strategies of selected EU countries: a status report on compliance with article 4 of the energy efficiency directive., B.P.I. Europe, Editor. 2014: Brussel.

[22] Winther, T. and K. Gurigard, Energy performance contracting (EPC): a suitable mechanism for achieving energy savings in housing cooperatives? Results from a Norwegian pilot project. Energy Efficiency, 2017. **10**(3): p. 577-596.

[23] de Wilde, P., The gap between predicted and measured energy performance of buildings: A framework for investigation. Automation in Construction, 2014. **41**: p. 40-49.

[24] Ástmarsson, B., P.A. Jensen, and E. Maslesa, Sustainable renovation of residential buildings and the landlord/tenant dilemma. Energy Policy, 2013. **63**: p. 355-362.

[25] Guerra Santin, O., Occupant behaviour in energy efficient dwellings: evidence of a rebound effect. Journal of Housing and the Built Environment, 2013. **28**(2): p. 311-327.

[26] Majcen, D., L.C.M. Itard, and H. Visscher, Theoretical vs. actual energy consumption of labelled dwellings in the Netherlands: Discrepancies and policy implications. Energy Policy, 2013. **54**: p. 125-136.

[27] Haas, R., H. Auer, and P. Biermayr, The impact of consumer behavior on residential energy demand for space heating. Energy and Buildings, 1998. **27**(2): p. 195-205.

[28] Hansen, A.R., K. Gram-Hanssen, and H.N. Knudsen, How building design and technologies influence heat-related habits. Building Research & Information, 2018. **46**(1): p. 83-98.

[29] ISSO, Energieprestatie advies woningen, in 82.3, ISSO, Editor. 2011: Rotterdam.

[30] Steemers, K. and G.Y. Yun, Household energy consumption: a study of the role of occupants. Building Research & Information, 2009. **37**(5-6): p. 625-637.

[31] ECN, Energy Efficiency trends and policies in the Netherlands. 2015, ECN: The Netherlands. p. 20.

[32] Field, A., Is ANOVA robust?, in Discovering statistics using IBM SPSS statistics, M. Carmichael, Editor. 2000, SAGE Publications Ltd: London. p. 444-445.

[33] Guerra Santin, O., L. Itard, and H. Visscher, The effect of occupancy and building characteristics on energy use for space and water heating in Dutch residential stock. Energy and Buildings, 2009. **41**(11): p. 1223-1232.

[34] van den Brom, P., A. Meijer, and H. Visscher, Performance gaps in energy consumption: household groups and building characteristics. Building Research & Information, 2017: p. 1-17.

[35] Guerra Santin, O., Behavioural Patterns and User Profiles related to energy consumption for heating. Energy and buildings, 2011. **43**: p. 2662-2672.

[36] Cheng, V. and K. Steemers, Modelling domestic energy consumption at district scale: A tool to support national and local energy policies. Environmental Modelling & Software, 2011. **26**(10): p. 1186-1198.

[37] ECN and Rigo, Energiebeparing: Een samenspel van woning en bewoner - Analyse van de module Energie WoON 2012. 2013.

[38] Chen, J., X. Wang, and K. Steemers, A statistical analysis of a residential energy consumption survey study in Hangzhou, China. Energy and Buildings, 2013. **66**(0): p. 193-202.

[39] Kaza, N., Understanding the spectrum of residential energy consumption: A quantile regression approach. Energy policy, 2010. **2010**(38): p. 6574-6585.

[40] Yohanis, Y.G., et al., Real-life energy use in the UK: How occupancy and dwelling characteristics affect domestic electricity use. Energy and Buildings, 2008. **40**(6): p. 1053-1059.

[41] Druckman, A. and T. Jackson, Household energy consumption in the UK: A highly geographically and socio-economically disaggregated model. Energy Policy, 2008. **36**(8): p. 3167-3182.

[42] Filippidou, F., N.E.T. Nieboer, and H. Visscher, Effectiveness of energy renovations: a reassessment based on actual consumption savings, in eceee. 2017: France.

[43] Azevedo, J.A., L. Chapman, and C.L. Muller, Critique and suggested modifications of the degree days methodology to enable long-term electricity consumption assessments: a case study in Birmingham, UK. Meteorological Applications, 2015. **22**(4): p. 789-796.

[44] Kane, T., S.K. Firth, and K.J. Lomas, How are UK homes heated? A city-wide, socio-technical survey and implications for energy modelling. Energy and Buildings, 2015. **86**: p. 817-832.

[45] Milne, G. and B. Boardman, Making cold homes warmer: the effect of energy efficiency improvements in low-income homes A report to the Energy Action Grants Agency Charitable Trust. Energy Policy, 2000. **28**(6): p. 411-424.

[46] Madlener, R. and M. Hauertmann, Rebound effects in German Residential heating: Do ownership and income matter? FCN Working paper, 2011. **2/2011**.

[47] Corrado, V. and E. Fabrizio, Assessment of building cooling energy need through a quasi-steady state model: Simplified correlation for gain-loss mismatch. Energy and Buildings, 2007. **39**(5): p. 569-579.

4 Variances in Residential Heating Consumption

Importance of Building Characteristics and Occupants Analysed by Movers and Stayers

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The previous two chapters showed discrepancies between actual and theoretical energy consumption and savings. Both acknowledged that the occupant has an influence on actual energy consumption; however, the extent of the influence is still not clear. Therefore, the aim of this chapter is to determine to what extent the occupant is responsible for the variance in energy consumption among buildings. We do this by examining two large datasets containing household and building characteristics as well as actual energy consumption data , originating from two different countries: the Netherlands and Denmark. The analyses show not only the influence of the occupant on the variance but also whether this influence differs if the buildings have different characteristics.

ABSTRACT

It is commonly accepted that occupants have a significant influence on the variation in residential heating consumption. However, the scale of that influence lacks empirical investigation. The aim of this study was to distinguish which part of the variance in actual residential heating consumption can be attributed to the occupants, and which part to the building itself. This was achieved by applying and extending a method suggested by Sonderegger in 1978, using updated and significantly improved data from two different countries: the Netherlands and Denmark. These data contain different types of heating supply systems (district heating and natural gas) and different housing forms (multi and single-family social housing, and private detached single-family houses). For the studied databases, the results indicate that approximately 50% of the variance in heating consumption between houses can be explained by differences related to occupants. The other 50% can be explained by the characteristics of the building itself and other physical parameters, which are often not taken into account in simulation models of heat transmission within buildings. Additional analyses indicate that the relative influence of occupants on heating consumption differs depending on the building characteristics of the dwelling. For example, the influence of occupants is larger when the building is more energy efficient. Based on the research results, it can be concluded that it is unrealistic to aim for a building simulation model that perfectly projects residential heating consumption for individual cases. However, creating building simulation models and occupant consumption profiles that accurately represent average residential heating consumption should be possible.

KEYWORDS Residential building; Space heating; Actual energy consumption; Building energy simulation; occupants

Nomenclature

DHW	=	domestic hot water
$Adjheat_t$	=	standardised heat consumption year t [kWh]
$heat_t$	=	annual heat consumption year t [kWh]
avg_heat_{2010}	=	average annual heat consumption of the year 2010 [kWh]
avg_heat_{2010}	=	average annual heat consumption of the year 2015 [kWh]
Cv	=	Coefficient of variance
Sd	=	Standard deviation
$Nheat_t$		normalised heat consumption year t [kWh]
c_t	=	constant, result from linear regression year t
b_t	=	coefficient, result from linear regression year t
LRC	=	logarithm of relative heat consumption
Var_{max}	=	maximum variance
σ^2_t	=	variance year t
$\sigma^2\left[LRC^{movers}\right]$	=	variance in heating consumption of 'movers' due to changes in heating consumption of the same occupants over time (SO) **and** variance due to changes in heating consumption due to new occupants moving into the house (NO)
$\sigma^2\left[LRC^{stayers}\right]$	=	variance in heating consumption of 'stayers': due to changes in heating consumption of the same occupants over time (SO)
$\sigma^2\left[Var_{\max}\right]$	=	maximum variance in heating consumption, when everything is different compared to the previous period. Due to changes in heating consumption of the same occupants over time (SO) **and** changes in heating consumption due to new occupants moving into the house (NO) **and** change of physical characteristics that are not taken into account in the linear regression model (Ph)
SO	=	changes in heating consumption over time of the same occupants [%]
NO	=	changes in heating consumption due to new occupants moving into the house [%]
Ph	=	Physical characteristics that are not taken into account in the linear regression analyses [%]
AB	=	building characteristics that were available in the database and are taken into account in the linear regression [%]

4.1 Introduction

Household energy consumption is estimated to be responsible for approximately 26% of the total energy consumption in Europe [1] . Therefore, policymakers see a large potential for energy savings in this sector. However, previous studies have indicated that thermal renovations often result in lower energy savings than expected [2]. This discrepancy between actual and theoretical savings is caused (among other factors) by the energy performance gap (EPG), which is the discrepancy between actual and calculated energy consumption of a household. The EPG illustrates that it is not possible to explain residential energy consumption by solely relying on building simulation models [3]. Several studies have also demonstrated that residential energy consumption varies largely due to the characteristics of the occupants as indicators of behavioural patterns [4-6]. For example incomes in England were found to be positively correlated with the actual energy consumption in a household [5] and a larger number of household members also results in higher energy consumption, but it decreases the energy consumption per person [6]. Age is found to be the most determining indirect effect on heating [4].

Based on previous studies, it is expected that occupants play an important role in this EPG, but the scale of this role is unclear [7]. Some researchers even expect the occupant role to be more important than the role of building characteristics [8, 9]. Sonderegger [10] was one of the first who attempted to define the extent to which occupants are responsible for the variance in energy consumption among similar houses, by studying *movers* (houses with changed occupants) and *stayers* (houses with the same occupant over time). Accordingly, Sonderegger compared the variance in energy consumption of houses with movers and houses with stayers. The aim of his method was to define the extent to which the variance in residential energy consumption was related to either occupants or building characteristics.

This study applies Sonderegger’s method to two significantly larger and more diverse datasets from the Netherlands and Denmark. This means that our data contains almost one million houses and households, compared to the 200 similar houses in Sonderegger’s study. This comparative design enables a stronger generalisability of the results, which is seldom seen in quantitative energy consumption studies. Because many researchers found a relation between building characteristics and occupant behaviour, the analyses are extended by studying whether the influence of occupant behaviour depends on the building characteristics.

By doing this, the importance of the role of occupants for understanding variation in energy consumption among households is indicated, and the interaction of different types of building characteristics with the behaviour of occupants is shown. Knowing how much of the variance in energy consumption is caused by occupants enables a better insight in how to interpret the energy consumption results and how much variance in energy consumption can be expected due to variation in occupant behaviour. The results also indicate over which range the energy simulation can expected to be assumed to be correct. Further, the paper will show which part of the variance can be explained by the physical characteristics that are not taken into account in the energy simulation.

This paper first reviews research studies investigating the influence of the occupant on residential energy consumption. This section is followed by an explanation of the data used for this study, an explanation of Sonderegger's method, and how this method is adapted to make it suitable for our datasets. Then, the results of the analysis are presented. In the discussion section, the authors consider both the advantages and disadvantages of the adapted method and the data used. Finally, conclusions are drawn in the final section.

4.2 Literature review

Many researchers have already investigated variations in residential energy consumption in similar dwellings, and sought to explain the reasons for the variance in energy consumption among similar dwellings. In this literature review, an overview of studies on this topic is provided, and the research results, applied methods, and type and origins of the data are discussed. The aim of this review is to indicate current knowledge about the influence of occupants on building-related energy consumption and to define how this study could contribute to further insights.

The literature for this review was selected based on the following conditions: First, the aim of the research must include a better understanding of residential energy consumption and the influence of occupants; Second, the research must be based on measured data/post-occupancy data. This means that studies using simulated data were excluded from this literature review. The reasoning behind this that the use of simulated data is a simplification of reality, and therefore does not reflect the complexity of actual energy consumption. Finally, only references from academic journal papers are used.

4.2.1 Comparing results

Table 4.1 shows a summary of the literature review, and the first column lists the aims of the study. Although the aims of the studies appear similar, the results and conclusions vary. All studies concluded that occupants and their behaviour play a significant role in the amount of residential energy consumption. However, the amount of the impact is different across the studies, with some claiming that occupants are the most influential factor. For example, Steemers and Yun [5] found that the roles of occupant behaviour and socio-economic factors are the most important components for determining residential energy consumption. According to their research, the physical characteristics of dwellings (such as construction year, type and floor area) are less important. However, it should be taken into account that they also considered that the type of heating and/or cooling system and its control to be a decision of the occupant, and thus a behavioural factor.

Other studies concluded that the building characteristics are the principal determining factor for residential energy consumption. For example, Guerra Santin et al. [11] found that 42% of residential energy consumption can be determined by the building characteristics, and only 4.2% by occupant characteristics. In this study, it has to be taken into consideration that Guerra Santin et al. [11] used the linear regression to determine those percentages with the building characteristics, and subsequently added the occupant characteristics. Therefore, they did not consider possible relationships between occupant behaviour and building characteristics. These results might have been different if they had started with the occupant characteristics. Huebner et al. [12] found that building characteristics account for approximately 39% of the variability in energy consumption, socio-demographic factors are 24%, heating behaviour is 14%, and attitudes and other behaviour account for only 5%. However, a combined model including all predictors explains only 44% of all variability. Sonderegger [10] found that 54% of the variance in energy consumption among similar buildings could be explained by “obvious building characteristics”, 15% by the change of occupants, 17% by lifestyle, and 13% by house-related quality differences. The obvious building characteristics referred to by Sonderegger include for example the number of bedrooms, which he takes into account by applying a regression analysis. House related quality differences are the physical characteristics of the house that are not considered in the regression model, for example, if a tree blocks the solar radiation. Further, Brounen et al. [13] found that residential heating consumption is primarily determined by the building characteristics, such as its construction year or type.

Other studies found the same (or almost the same) impact level of building and occupant characteristics on residential energy consumption. For example, Verhallen and Raaij [14] discovered that household behaviour explains 26% of residential energy consumption, and house characteristics explain 24%. They also found an interaction between building characteristics and residential energy consumption. As an illustration, house insulation has a positive effect because people tend to lower their thermostat settings more often, and they are more likely to open their windows more frequently. Similarly, a recent study [15] investigated how occupant behaviour is related to building characteristics (including heating and ventilation installations and building year). Gill et al. [16] found that energy efficiency behaviour accounts for 51% of the variance in heat consumption between dwellings. However, they explicitly state that behaviour is not claimed to be the dominant factor.

Several aspects can explain why the conclusions differ although the aim of the studies is similar. For example, the sample size and the level of detail of the collected data differ significantly between studies. Comparing the research of Spataru et al. [17] and the study of Brounen et al. [13] similar aims can be ascertained, but the data and focus of the researchers are completely different. The first used highly detailed monitoring data from a single house, while the latter used a large but more aggregated database containing information of one million houses and their occupants. Unavoidably, this results in different types of research and different research results.

In addition, the starting point of the researcher (and the definition of the influence of the occupant on residential energy consumption) can mean that those studies with similar aims arrive at different conclusions. For example, all studies indicated that occupants have a significant influence on residential energy consumption. However, there is discussion about the magnitude of this influence, and whether it is more influential than, building characteristics. One of the reasons for these different research results is the different starting point of the research. Some researchers take the house and its physical characteristics as a starting point [18], while others focus on the occupant. Here, they assume the occupant chooses the house and therefore the influence of this choice is part of the influence of the occupant on residential energy consumption [8]. Often, when the first starting point is applied, the building characteristics seem to be more important. Conversely, when the second starting point is applied, occupant influence appears to be more important. Several studies have indicated an awareness of these direct and indirect effects [5, 9, 20]. For example: Steemers and Yun [5] demonstrated that behavioural, physical and socio-economic parameters have direct and indirect influence of energy use; and Estiri [20] showed that household characteristics have almost the same impact on building energy consumption as building characteristics, if not only their direct effect but also their indirect effects are taken into account.

4.2.2 Occupant characteristics

Many of the studies use occupant characteristics to indicate the influence of the role of occupants on residential energy consumption. The main reason for this is that occupant characteristics are easier to collect than (for example) detailed behavioural indicators, and they are available for a higher number of households. As several studies suggest that occupant characteristics indicate occupant behaviour, it also appears a sensible approach. Several occupant characteristics are found to correlate with actual energy consumption. The strongest and most frequently-mentioned correlations are those between the number of occupants [4, 12, 18-24], and income [5, 12, 19, 20, 22, 25].

4.2.3 Statistical methods

While the studies have differences in data and focus, their statistical methods are similar. Almost all studies use cross-sectional statistical analysis[5] techniques, with the majority using linear regression or multiple linear regression analysis. Within studies on the impact of prices on residential energy consumption, panel data are more frequently used [26, 27]. In our literature review, only the study of Sonderegger [15] makes use of longitudinal/panel data[6]. In his research, 205 similar houses were monitored for 3 years (1971-1973). The resulting data included energy consumption figures, building characteristics, and which occupants were living the house during the monitored years. The research is based on the assumption that if the occupants remain the same, energy consumption will be more constant over time than if they move and are replaced by other occupants.

Conducting energy consumption research can benefit significantly from longitudinal data and the accompanying statistical data analysis techniques. In the past, many studies used data from similar houses to compare the influence of the occupant on residential energy consumption. However, no houses are exactly similar, owing to different locations and layouts. Therefore, longitudinal data and the accompanying statistical data analysis techniques are highly beneficial for conducting energy consumption research. For example, multiple houses over time can be monitored, and the direct influence of the building characteristics can be excluded from the

5 *Cross sectional data is data of many different subjects at the same point of time*

6 *Longitudinal/panel data is data of many different subject that are followed over multiple points in time*

analysis because these factors remain the same (assuming that the house is not renovated). This presents significant potential for evaluating the effect of policy changes, newly installed technologies and renovations.

4.2.4 Conclusions of the literature review

Based on this literature study, it can be concluded that determining the effect of the occupant behaviour on residential energy consumption is highly dependent on the boundaries that the researcher set for the term occupant influence. The results of determining the influence of occupants on residential energy consumption varied from 4.2% to more than 50%. Furthermore, if longitudinal data are available then the research should benefit from its possibilities. Further, most studies on the influence of occupants on residential energy consumption are based on one dataset from one country or region. Moreover, the literature review indicates that all studies acknowledge that occupants affect actual energy consumption but the degree of influence varies between the studies. A lack of large databases and detailed building and occupant data makes it difficult to establish a constant value or even a range for such influence, since many of the previous studies have been conducted on small databases.

TABLE 4.1 Literature overview of studies that aim to get a better insight into residential energy consumption and the reason for the variance in energy consumption among similar dwellings

Aim/research question	Data, type, country	Method	Conclusion	ref
to determine the factors responsible for the remaining 46% variation that cannot be explained by conventional factors.	– Twin rivers project, 248 townhouses, – monthly electric and natural gas meter readings – UK	regression, three-factor multiplica-tive model	54% of the variance is explained by obvious building characteristics, change of occupants explains 15%, lifestyle explains 17% and persistent house-related quality differences explain 13%.	[10]
to determine the factors that determine energy use for home heating are investigated in this study.	– 145 similar houses 79 with standard insulation and 78 with superior insulation. – Natural gas meters, 4 moments in time – The Netherlands	factor analysis	– Home characteristics, special circumstances, and sociodemographic together explain 58 % of the energy use variance. – Household behaviour alone explains 26 % – home characteristics alone 24 % – special circumstances alone explain 11 % of the energy-use variance	[14]

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TABLE 4.1 Literature overview of studies that aim to get a better insight into residential energy consumption and the reason for the variance in energy consumption among similar dwellings

Aim/research question	Data, type, country	Method	Conclusion	ref
to determine to what extent consumer behaviour influences space heating energy demand and test the linear approach describing space heating energy demand by means of a simple linear dependence on climate (heating degree days) and the thermal quality of a building (heat load).	– 400 households – Data on energy consumption (without electricity demand for appliances) by fuel type are available for at least 1 year, in most cases for 2 or 3 years. sociological, and structural data – Austria	service factor analysis	– The result of this investigation provides evidence of a rebound-effect of about 15 to 30% due to building retrofit.	[28]
to determine to what extent energy performance is determined by interactions between occupants, behaviour and buildings systems, as well as building and climate characteristics establish.	– 3358 housing units for heating and 2718 housing units for cooling climate – actual energy consumption data for heating and cooling and building, occupant behaviour and socioeconomic characteristics data – 50 states in US	regression models and path analysis	– Climate and building characteristics alone are insufficient as determinants of energy demand. – Most significant parameter is climate. Second is a set of parameters related to occupant behaviour, specifically in terms of the choices made about heating and cooling systems and their control – Less important than might be expected are some physical characteristics of the dwellings	[5]
to gain greater insight into the effect of occupant behaviour on energy consumption for space heating by determining its effect on the variation of energy consumption in dwellings while controlling for building characteristics	– 15000 interview-based survey – 3 years of heating (gas consumption data) including household characteristics and use of the dwelling, – the Netherlands	ANOVA & multiple regression analysis	– building characteristics determine 42% of the energy use in a dwelling – adding occupant characteristics and behaviour increases the explanation factor with 4.2%	[11]
to determine the direct, indirect, and total impacts of household and building characteristics on residential energy consumption	– microdata from the 13th Residential Energy Consumption Survey (RECS) – total household energy consumption – US	structural equation modelling	– the direct impact of household characteristics on residential energy consumption is significantly smaller than the indirect impact. – Taking both direct and indirect impact into account the total impact of households on energy consumption is only slightly smaller than that of building characteristics.	[20]

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TABLE 4.1 Literature overview of studies that aim to get a better insight into residential energy consumption and the reason for the variance in energy consumption among similar dwellings

Aim/research question	Data, type, country	Method	Conclusion	ref
understanding the spectrum of residential energy consumption	– residential Energy Consumption Survey (RECS) public use microdata set – total household energy consumption – US	quantile regression analysis	– Results show that housing size matters for space conditioning – housing type has a more nuanced impact. – Some, not all, types of multifamily housing offer almost as much savings as a reduction in housing area by 100 m2, compared to single-family houses.	[24]
Identifying the key determinants and effects of occupants' behaviour on energy use for space heating	– 313 household – annual gas consumption – the Netherlands	Pearson correlation samples t-test, ANOVA, Chi-square regression model	– Interaction between occupant behaviour and building characteristics are found – occupant behaviour (indirect and direct) can predict 11,9% of the variation in energy use.	[18]
to evaluate the relationships between occupancy and energy usage, as well to diagnose the performance and energy efficiency	– 1 house, one family was extensively monitored – energy consumption for heating – UK		– In order to reach the 2050 target to reduce carbon emissions by 80%, the behaviour of the occupant is increasingly important, being responsible for the energy consumption in the building.	[17]
the contribution of behaviours to actual performance	– 26 similar dwellings – domestic electricity heat and water consumption and occupant behaviour – UK	linear regression	– Energy-efficiency behaviours account for 51% of the variance in heat consumption in dwellings – 37% of the variance in electricity consumption can be explained by energy behaviour – and 11% of the variance in water consumption can be explained by energy behaviour.	[16]
to identify the influences of the occupant behaviour on the building energy consumption.	– annual building energy use intensity (EUI) 2003 – annual energy consumption – Japan	cluster analysis, Grey relational analysis	– Weather conditions significantly influenced occupant behaviour, thereby impacting building energy consumption. – Households tended to maintain their lifestyles, and the level of their general indoor activities associated with these end-use loads did not fluctuate widely from month to month.	[29]
to determine if energy efficiency of appliances and houses or user behaviour is the more important	– 50000 households – meter readings heating and electricity consumption, socio-economic information on their inhabitants, building information – Denmark	regression and literature study	– user behaviour is at least as important as the efficiency of technology when explaining households' energy consumption in Denmark.	[8]

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TABLE 4.1 Literature overview of studies that aim to get a better insight into residential energy consumption and the reason for the variance in energy consumption among similar dwellings

Aim/research question	Data, type, country	Method	Conclusion	ref
Determining the extent to which the use of gas and electricity is determined by the technical specification of dwellings as compared to the demographic characteristics of the residents.	– 3000000 Dutch homes and their occupants – annual gas and electricity consumption – the Netherlands	regression	– Residential gas consumption is determined principally by structural dwellings characteristics, such as the vintage, building type, and characteristics of the dwelling, – while electricity consumption varies more directly with household composition, in particular income and family composition.	[13]
to determine the impact of occupants on residential energy consumption in China.	– 642 surveys related to behaviour and energy use in winter and 838 surveys in summer – household energy data building and occupant characteristics and behaviour – China, Hangzhou	bivariate correlation, path, and multiple linear regression analysis	– household socio-economic and behaviour variables are able to explain 28.8% of the variation in heating and cooling energy consumption.	[21]
to what extent different types of variables (building factors, socio-demographics, attitudes and self-reported behaviours) explain annualized energy consumption in residential buildings	– data from a sample of 924 English households collected in 2011/12 – annual energy consumption – England	lasso regression	– Building variables on their own explained about 39% of the variability in energy consumption – socio-demographic variables 24% – heating behaviour 14% – attitudes &other behaviours only 5%. – a combined model encompassing all predictors explained only 44% of all variability, indicating a significant extent of multicollinearity between predictors.	[12]
socio-cultural differences in heat consumption	– household data and building characteristics data – households' annual heat consumption for space heating and heating of hot water – Denmark	regression	– households' heat consumption levels vary across social groups – social groups indicate differences in heating-consuming habits.. – the results of the paper indicate that around one-third of the impact of educational and income differences between households on heat consumption are due to differences in heat-consuming habits (direct effect), whereas the rest, two thirds, are due to differences in households and houses (indirect effects)	[19]

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TABLE 4.1 Literature overview of studies that aim to get a better insight into residential energy consumption and the reason for the variance in energy consumption among similar dwellings

Aim/research question	Data, type, country	Method	Conclusion	ref
to provide a better understanding of the main determinants of residential energy consumption in order to guide energy policymaking.	– survey data 36000 occupants, national housing survey – household energy consumption – France	Multiple Correspondence Analysis and Ascending Hierarchical Classifications, OLS regression.	– energy prices were the most important factors determining domestic energy consumption. – Occupant characteristics significantly affect domestic energy use.	[30]

4.3 Data

Two databases are used in this study: one with data from Dutch houses and households and one from Danish houses and households. This section explains the two datasets and how they are used in this study. The first part explains the Dutch database and the second part the Danish database.

4.3.1 Dutch data

The Dutch data originate from two different sources. The first one is the SHAERE database, which is a database from Dutch social housing organisations in the Netherlands. It is primarily used to monitor energy efficiency and contains 60% of the Dutch social housing stock. Of the total housing stock, social housing stock in the Netherlands is relatively large compared to other countries, accounting for 30%. This means the database contains a significant share of all houses in the Netherlands. Within these houses in the database, 46.9% are single family houses and 53.1% are multi-family houses. For single-family houses, the vast majority are terraced. The database contains most of the input variables that are used to calculate the energy performance of houses, the energy performance certificate, and predicted energy consumption per house for six years (2010-2015). This dataset is combined with actual annual energy consumption data from Statistics Netherlands. Energy consumption data are considered private (sensitive information); therefore, it is only allowed to publish the results on an aggregated level. Apart from actual energy consumption data the Statistics Netherlands database also contains occupant characteristics data (such as income, number of household members, and employment status).

Approximately 95% of Dutch households use gas as a heating source for their house [31]. In countries such as the Netherlands and Denmark, energy for heating constitutes the main energy demand of a house. Further, energy consumption for heating has the highest energy performance gap. Therefore, only houses that use gas as a heating source are studied. This enables us to distinguish energy consumed for heating and domestic hot water (and sometimes cooking) on one side and energy consumed for electrical appliances on the other side. Because domestic hot water is on average a relatively small part of the gas consumption of Dutch houses from now gas consumption will be referred to as the energy used for heating. However the amount of gas consumption for domestic hot water is significant (in the Netherlands on average 16%) and therefore it is important that the reader should be aware that this is included in the term “heating consumption” [32]. Energy supply companies in the Netherlands are only obligated to report actual energy consumption every three years. If the data is not reported, energy consumption data of the previous year is used and therefore all cases with exactly the same gas consumption as the previous year are deleted (approximately 15% of the total amount of cases). It is assumed highly unlikely that a household would use precisely the same amount of gas every year.

Houses with collective installation systems are deleted from the database because the Dutch statistical experts expressed doubts about the quality of this data. Further, because the databases that we use are relatively large, there is an increased probability of them recording unrealistic values that might affect the results. To avoid possible bias of those unrealistic values and errors biasing the results, the highest and lowest 1% of household energy consumption (kWh) and area (m^2) are removed for each year in the analysis. Because the relative energy consumption is used in this study (explained in section 5 energy consumption 2015/energy consumption 2010), cases with a relative consumption higher than 12 were deleted. This is because some extreme values were found that are highly unlikely and yet have a significant influence on the mean (891 cases), so they can be considered outliers. For this analysis, it is important that the building characteristics are constant. Therefore, dwellings with changed building characteristics (such as renovations or administrative corrections) are deleted (approximately 30% of the cases). Finally, only cases that had at least an energy consumption record for the years 2010 and 2015, and a theoretical energy consumption record for at least one year are taken into account. After filtering, data on 375,382 houses remained.

4.3.2 Danish data

The Danish data came from two sources. Data on building and household characteristics were taken from Statistics Denmark's administrative registers, which covers the full population. These were merged with data on household energy consumption for space heating and hot water from the Danish Building and Dwelling Register (BBR), which is part of the Danish Ministry of Taxation. Heat supply utilities in Denmark are required by law to submit household energy consumption data to BBR, who subsequently compile and prepare data for research and other purposes. The administrative data from Statistics Denmark is accessible in anonymised form through an online server.

The data are registered on housing units. Therefore, the used data on energy consumption is from single-family detached houses that are individually metered to avoid uncertainties about which households the consumption relates to. Single-family houses are the predominant type of housing in Denmark, accounting for 44 % of the housing stock in 2014 (Statistics Denmark). Further, in the Danish sample, 92.57 % of the houses are owner-occupied. Data for houses with an individual heat supply (for example oil-fired boiler) has some uncertainties regarding the periodisation of yearly energy consumption because it is not clear at what time the fuel is used. Therefore, data is restricted to houses supplied with district heating or gas, which together supplied 78 % of Danish households in 2015 (Statistics Denmark). By law, all households in Denmark have individual metering of their energy consumption, independently if the supply is by gas or by district heating. By restricting the study to households supplied with district heating, or a gas supply that has registered heat consumption, the data covers approximately 64% of all single-family detached houses in Denmark. It is not possible to distinguish between energy used for space-heating and domestic hot water, but it is estimated that space-heating accounts for approximately 80%, while the remainder is for domestic hot water [33]. However, in newer houses the percentage attributes to space heating might be lower due to their higher energy efficiency. To mitigate the risk of unrealistic values and errors biasing the results, the highest and lowest 1% of household energy consumption (kWh) and areas (m^2) are removed for each year in the analysis. Moreover, the sample was restricted to domestic housing, not for business. Further, if the house had no registered occupants, its data were removed from the sample. Taken together, this removed approximately 17 % of the observations. Finally, 1,425 observations were removed because their consumption in 2015 was more than five times higher than in 2010. Also 27,547 observations were removed because they did not have the same building characteristics registered in 2010 and 2015. After filtering, data of 512,393 houses remained.Table 4.2 shows the variables used in the regression as building characteristics.

TABLE 4.2 Variables used in the regression model as building characteristics for Danish dataset

Variable name	Variable description	Categories
gas	Heating supply: natural gas or district heating?	0= District heating; 1=Natural gas
area	Heated area (m2)	Continuous
rooms	Number of rooms	Count
woodstove	Do the house have a woodstove or fireplace?	1=yes
Attic floor	Do the house have an attic floor?	1=yes
basement	Do the house have a basement?	1=yes
roof	Roof material	1=fibrecement; 2=cement stone; 3=tile, 4=other material
exteriorwall	Exterior wall material	1=Bricks; 2=Wood; 3=Concrete; 4=Other material
building-period7a	Building period in 7 categories	1=<1938; 2=1938-1960; 3=1961-1972; 4=1973-1978; 5=1979-1998; 6=1999-2006; 7=>2006

4.4 Method

This section explains the method used in this study, which is based on the method proposed by Sonderegger [10]. This method is based on the difference in variance between movers and stayers. Therefore, this methodology section starts by describing how movers and stayers are identified. This is followed by an explanation of Sonderegger's method, which describes step-by-step how the method was applied, and how it was made applicable for our data. This description also explains why the variance in relative heat consumption instead of the average relative heat consumption is studied (heat consumption 2015 divided by heat consumption 2010). Further, it should be mentioned that when heating consumption is referred to in the text, this also includes energy consumption for domestic hot water. This is included because the amount of energy consumed for hot water is relatively small compared to energy used for heating (approximately 20%) [33]. Energy for *Domestic Hot Water* (DHW) is, compared to energy for heating, less dependent on the technical characteristics of a building. The amount of energy consumption for DHW will be relatively large for energy-efficient buildings compared to relatively energy-inefficient buildings, because the energy demand for heating is in energy-efficient buildings is lower than in energy-inefficient buildings, while the domestic hot water demand is not influenced by the energy-efficiency of the building. This is something to be aware of because it allows for possible bias.

4.4.1 Identifying movers and stayers

To identify movers and stayers in the databases, it was determined whether the reference person in a household stayed the same or changed between 2010 and 2015. For the Dutch case, the reference person of a house is already identified in Statistics Netherlands data. For the Danish case, the oldest person in the house is selected as the reference person (if two people have exactly the same age, one is randomly chosen). This method could cause some bias because it is possible that the reference person will leave the house but the others will stay (or the other way around). However, given the large size of the datasets, this is considered acceptable, and so the authors do not expect those cases to influence the results significantly.

4.4.2 Method description

The starting point of Sonderegger's method is the assumption that the heat consumptions of two different time periods will have a higher correlation for houses with the same occupant than for houses with different occupants, because occupants continue to have the same behaviour over time. To investigate this, a comparison is made of the variance in relative heat consumption of a group of houses where occupants remained the same (stayers) and a group where occupants changed (movers). The variance of relative heat consumption and not the mean is chosen for study, because the variance shows how far the relative heat consumption of different cases is distributed. A large variance would mean that the spread of the relative heating consumption is wide, whereas a small variance would mean the opposite (Figure 4.1)

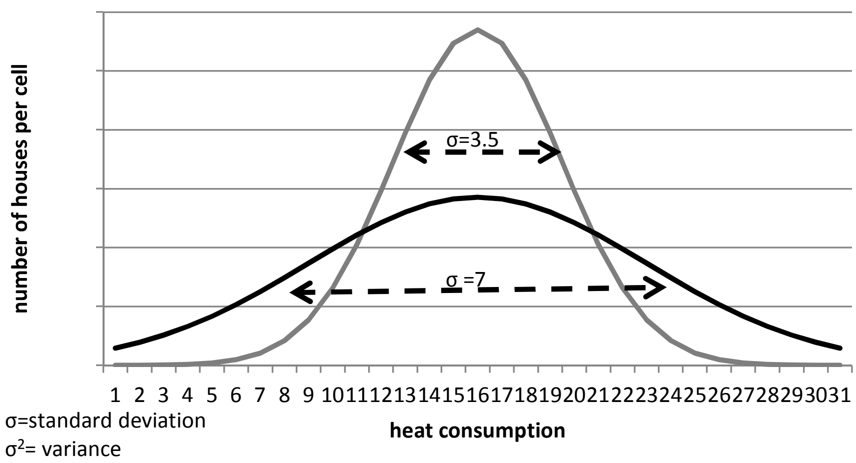

FIG. 4.1 Fictive normal distributions to show the effect of data with the same mean but a different variance

The analyses used heat consumption data from 2010 and 2015. To make the heat consumption of those two years comparable, a standardization method is applied: the heat consumption of 2015 is multiplied by the ratio of the means of the years 2010 and 2015 (Eq. 4.1), Doing this ensures the removal of variances in heat consumption due to weather and other external factors.

$$adjheat_{2015} = heat_{2015}\left(\frac{avg\_heat_{2010}}{avg\_heat_{2015}}\right) \qquad \text{EQUATION 4.1}$$

$adjheat_{2015}$ = standardised heat consumption 2015
avg_heat_{2010} = average annual heat consumption 2010
avg_heat_{2015} = average heat consumption 2015
$heat_{2015}$ = annual heat consumption 2015 for individual house

The standardisation is followed by a linear regression, where the dependent variable = actual heat consumption, and the independent variable = theoretical heat consumption/building characteristics. This linear regression is conducted for two reasons: 1. To determine which part of the variance in energy consumption for heating can be explained by the available building characteristics (AB) in the database; and 2. To make the buildings comparable. The regression coefficients are used to normalise the heating consumption, which makes the buildings comparable even though they have different building characteristics.

$$Nheat_{2010} = c_{2010} + b_{2010} \cdot heat_{2010}$$ EQUATION 4.2

$$Nheat_{2015} = c_{2015} + b_{2015} \cdot adjheat_{2015}$$ EQUATION 4.3

$Nheat_t$ = normalised heat consumption year t
c_t = constant, result from linear regression year t
b_t = coefficient, result from linear regression year t

Then, the relative heat consumption is determined, which is the normalised heat consumption of 2015 divided by the normalised heat consumption of the year 2010 (Eq. 4.4). When the relative heat consumption is close to one it means the heat consumptions of 2010 and 2015 are similar, whereas values of lower than one means the heat consumption of 2015 was lower than in 2010. Further, a figure higher than one means the heat consumption of 2015 was higher than in 2010. To make the data useful for further comparison, the natural logarithm of the relative consumption is calculated.

$$LRC = \ln\left(\frac{Nheat_{2015}}{Nheat_{2010}}\right)$$ EQUATION 4.4

LRC = logarithm of relative heat consumption

This makes the variance of relative heat consumption of movers and stayers comparable. However, to determine how much influence the movers and stayers have on the variance, first the maximum possible variance has to be determined. This maximum possible variance is determined by adding up the variance of movers in 2010 and 2015[7]. This would be the variance if the consumption level of each house in the second period were totally unrelated to its own level in the first period. Because the logarithm of relative heat consumption is used also the variance of the logarithm of heat consumption for 2010 and 2015 should be used.

$$Var_{\max} = \sigma^2_{2010} + \sigma^2_{2015}$$ EQUATION 4.5

7 Based on the law of propagation of variance of uncorrelated factors

Var_{max} = maximum variance
σ^2_t = log variance year t

The following assumptions are crucial for understanding how to define which part of the variance in heating consumption is due to occupants and which part is due to the building characteristics. This study assumes that the heat consumption in houses with the same occupant(s) (stayers) for the two periods would result in a higher correlation of heat consumption between those periods than that in houses with changed occupant(s) (movers). This assumption is made because occupants are expected to have a rather stable heating consumption pattern over time, for example, due to energy consumption practices and comfort expectations that gets embodied and 'carried' from one situation to the next [34, 35]. Energy consumption practices refer to routinized forms of behaviour that occupants perform in their everyday life, and although such practices have some continuity over time, they are also in constant change, for example in relation to new material surroundings [36, 37]. Therefore, occupants are expected to change consumption patterns over time, especially when moving into a new house. Thus, this study distinguishes between two types of changes over time. The first type relates to houses where the occupants do not move, which is expressed in the variance of the logarithm relative heating consumption of the stayers in this research. To these occupants the changes will be referred to as '*changes in heating consumption of the same occupants over time*' (SO). The second type relates to houses where the occupants change because new occupants move in (movers). It is expected that the practices performed by the previous (in 2010) and the new occupants (in 2015) have some similarities because they are performed in more or less the same material surroundings. However, it is also expected that the heating consumption in the 'movers' group changes over time because the occupants in the house are new due to the interaction between the practices that the occupants 'carry' with them and the new material surroundings of the occupants, resulting in completely different consumption patterns. These changes are referred to as '*changes in heating consumption due to new occupants*' (NO). Finally, the linear regression is demonstrated on the variances due to '*available building characteristics*' (AB). For the Dutch case, theoretical heat consumption was available, and for the Danish case, the characteristics are mentioned in Table 4.2. However, the '*available building characteristics*' (AB) in the databases are probably not the only physical characteristics that explain part of the variance in energy consumption among houses. It is expected that there will be other physical aspects that account for the variance of heat consumption, which will be indicated by the maximum variance in heat consumption. Based on these assumptions, the variance in heat consumption can be explained as follows:

$\sigma^2\left[LRC^{stayers}\right]$ = variance in heating consumption of ‘stayers’: due to changes in heating consumption of the same occupants over time (SO)

$\sigma^2\left[LRC^{movers}\right]$ = variance in heating consumption of ‘movers’ due to changes in heating consumption of the same occupants over time (SO) and variance due to changes in heating consumption due to new occupants moving into the house (NO)

$\sigma^2\left[Var_{\max}\right]$ = maximum variance in heating consumption, when everything is different compared to the previous period. Due to changes in heating consumption of the same occupants over time (SO) **and** changes in heating consumption due to new occupants moving into the house (NO) **and** change of physical characteristics that are not taken into account in the linear regression model (Ph)

Following these assumptions, it is possible to calculate how much of the variance is due to ‘changes in heating consumption of the same occupants over time’ (SO), ‘changes in heating consumption due to new occupants’ (NO), and ‘Physical characteristics that are not taken into account in the linear regression analyses’ (Ph). Additionally, there are the results of the linear regression, which indicates how much of the variance can be explained by the building characteristics that are taken into account in the linear regression (AB).

$$SO = \frac{\sigma^2\left[LRC^{stayers}\right]}{\sigma^2\left[Var_{\max}\right]} \cdot \left(1 - R^2\right) \qquad \text{EQUATION 4.6}$$

$$NO = \frac{\sigma^2\left[LRC^{movers}\right] - \sigma^2\left[LRC^{stayers}\right]}{\sigma^2\left[Var_{\max}\right]} \cdot \left(1 - R^2\right) \qquad \text{EQUATION 4.7}$$

$$Ph = \frac{\sigma^2\left[Var_{\max}\right] - \sigma^2\left[LRC^{movers}\right]}{\sigma^2\left[Var_{\max}\right]} \cdot \left(1 - R^2\right) \qquad \text{EQUATION 4.8}$$

$AB = R^2$ of linear regression

To investigate whether the influence of the occupant changes for different type of building characteristics, exactly the same procedure on a split file per building characteristics category is conducted. When the entire procedure is conducted for every building characteristics and each category, the differences per building category characteristics can be compared. The categories we investigated are as follows:

1. Energy label (Dutch data)
2. Construction year (Dutch and Danish data)
3. Building type (Dutch data)
4. Heating system (Dutch and Danish data)
5. Ventilation system (Dutch data)

4.5 Results

This section presents the results of the different analyses. It starts by showing the general results for both databases, and also describe the intermediate steps. These results are followed by the results per building characteristic. The first building characteristic that is explored is the energy label, followed by the construction period, dwelling type, type of heating system, and type of ventilation system. Depending on data availability, the analyses are executed either on both databases or on the Dutch database.

4.5.1 General results (full dataset)

As described in the method section, first the heating consumption for 2015 is standardized (Eq. 4.1). The results are presented in Table 4.3, which indicate that the coefficients of variances of 2010 and 2015 are similar, which means that the spread of the consumption is equal for both years.

TABLE 4.3 Standardising heating consumption

		Full sample (N=373,582)	Full sample (N=512,393)
		The Netherlands	Denmark
2010	Mean [kWh]	13,963.7	19,284.3
	Standard deviation	5,969.3	7,672.0
	Coefficient of variance	0.427	0.398
2015	Mean [kWh]	9,909.1	16,267.4
	Standard deviation	4,379.2	6,365.2
	Coefficient of variance	0.441	0.391
2015 adjusted*	Mean [kWh]	13,963.7	19,319.9
	Standard deviation	6,158.4	7,559.6
	Coefficient of variance	0.441	0.391

** 2015 values multiplied by the ratio of the means*

After this, a linear regression for 2010 and 2015 is conducted, with actual heat consumption as a dependent variable. The independent variables that are used for the regressions are different for the Dutch and the Danish cases due to data availability. For the Dutch case the energy performance of a house which is often referred to as "theoretical heating consumption" is used. The theoretical heating consumption is calculated based on the building characteristics, using the method described in ISSO-publication 82 [38], with the main aim to determine the energy performance certificate of Dutch dwellings (because the theoretical energy consumption is based on all available building characteristics available in the database). For the Danish case, the parameters indicated in Table 4.2 are used. With this regression it can be determined how much of the variance in heating consumption can be explained by the available building characteristics (average R^2 of regression models). The regression results indicate that the "theoretical heating consumption" explains (on average) 22.7% of the variance in heating consumption for the Dutch case, and 28.2% for the Danish case. The results of the regression (constant and B coefficient) are also used to correct for the building characteristics (Eq. 4.2 and Eq. 4.3). The regression results can be found in the Appendix in Tables 4.7, 4.8 and 4.9. After correcting the heating consumption for building characteristics, the results in Table 4.4 demonstrate (as expected) that the variance and means for both years and for movers and stayers are close.

TABLE 4.4 Normalised heating consumption for movers and stayers in the Netherlands and Denmark

		Stayers (Netherlands)			Movers (Netherlands)			Stayers (Denmark)			Movers (Denmark)		
		Sample (N=254,056)			Sample (N=121,326)			Sample (N=389,890)			Sample (N=122,503)		
2010	Mean	98.855	±	0.076	101.513	±	0.115	99.380	±	0.053	102.377	±	0.101
	Sd	38.211	±	0.054	40.155	±	0.082	33.324	±	0.038	35.324	±	0.071
	Cv	0.387	±	0.001	0.396	±	0.001	0.335	±	0.000	0.345	±	0.001
2015	Mean	101.034	±	0.080	96.944	±	0.118	100.306	±	0.053	99.212	±	0.096
	Sd	40.411	±	0.057	40.982	±	0.083	33.217	±	0.038	33.473	±	0.068
	Cv	0.400	±	0.001	0.423	±	0.001	0.331	±	0.000	0.337	±	0.001

Sd = standard deviation; Cv = coefficient of variance. Error standard deviation was estimated by Sd/sqrt(2N), error the mean Sd/sqrt N and error of coefficient of variation is error Sd/mean.

To identify how the heating consumption of 2010 and 2015 in the movers and stayers groups relate to each other, the relative heating consumption is calculated. This is the heating consumption of 2015 divided by the results for 2010. A natural logarithmic value is used to make the data useful for further comparison (Eq 4.4). A comparison of the natural logarithmic relative heating consumption for movers and stayers with each other shows that the variance differs between movers and stayers. This is an indication that (as assumed) the correlation of heating consumption of stayers between one year and another is higher than the correlation of houses with different occupants (Table 4.5).

TABLE 4.5 Relative heating consumption of stayers and movers in the Netherlands and Denmark

	Stayers (Netherlands)			Movers (Netherlands)			Stayers (Denmark)			Movers (Denmark)		
	Sample (N=254,056)			Sample (N=121,326)			Sample (N=389,890)			Sample (N=122,503)		
	LRC			LRC			LRC			LRC		
Mean	0.011	±	0.001	-0.066	±	0.002	0.0102	±	0.001	-0.030	±	0.001
Standard deviation	0.384	±	0.001	0.574	±	0.001	0.379	±	0.000	0.450	±	0.001
Variance	0.147	±	0.049	0.329	±	0.018	0.143	±	0.042	0.203	±	0.030

Now the relative heating consumption for movers and stayers is known, the linear regressions show how much of the variance can be explained by the available building characteristics. Next, the maximum possible variance in heating consumption is defined for the occupant, and building characteristics that were not the same over the years. This will enable determining how much of the variance is explained by the physical characteristics that were not available in the database (which are the characteristics not considered in previously- conducted linear regressions). This is achieved by adding the variance of the heating consumption in 2010 from the movers group together with the variance in heating consumption in 2015. For reasons of comparison, the natural logarithmic variance in heating consumption is used (Table 4.6).

TABLE 4.6 Logarithm normalised heating consumption of movers in the Netherlands and Denmark

		Movers (Netherlands) LNG			Movers (Denmark) LNG		
		Sample (N=121,326)			Sample (N=122,503)		
2010	Mean	4.529	±	0.001	4.559	±	0.001
	Standard deviation	0.473	±	0.001	0.399	±	0.001
	Variance	0.224	±	<0.001	0.159	±	<0.001
2015	Mean	4.461	±	0.001	4.530	±	0.001
	Standard deviation	0.547	±	0.001	0.393	±	0.001
	Variance	0.299	±	<0.001	0.154	±	<0.001

Following Sonderegger's method, it is assumed that the maximum variance of heating consumption is the sum of three factors:

1. "**changing heat consumption over time of the same occupants**" (SO): time-dependent variable for the *i*th house
2. "**changing heat consumption due to new occupants moving into the house**" (NO): of the occupant of the *i*th house, independent of time
3. "**Physical characteristics that are not taken into account in the linear regression analysis because they were not available in the database"** (Ph) of the *i*th house, time independent.

The variance of relative heating consumption of movers is the sum of two factors:

1. "**changing heat consumption over time of the same occupants**" (SO): time-dependent variable for the *i*th house
2. "**changing heat consumption due to new occupants moving into the house**" (NO): of the occupant of the *i*th house, independent of time

Finally, the variance of relative heating consumption of stayers is:

1. "**changing heat consumption over time of the same occupants**" (SO): time-dependent variable for the *i*th house

Based on these assumptions it can be calculated which part of the variance is caused by which factor. However, it should be remembered that the available building characteristics have been corrected by using the linear regression results. Equations 4.6, 4.7 and 4.8 show how the amount of influence of each parameter is calculated. The results are shown in Figure 4.2. For the Dutch case: 28% of the variance can be explained by changes in heating consumption due to new occupants over time (NO); 22.6% by changes in heating consumption of the same occupants over time (SO); 29.9% by physical characteristics not available in the database (Ph); and 19.5% by the building characteristics that were available in the databases (AB). For the Danish case: 33.7% of the variance is explained by changing heating consumption patterns of the same occupants over time (SO); 14.1% by changing heating consumption patterns due to new occupants (NO); 25% by physical characteristics that were not available in the database (Ph); and 27.3% by available building characteristics (AB). The use of different prediction variables for the linear regression that determines the influence of available building characteristics explains why there are different percentages for the categories: "*available building characteristics*" and "other physical characteristics" for the Dutch and the Danish case. However, for occupant behaviour, large differences were also found between the Dutch and Danish cases. A possible explanation for this could be the origin of the data. The Dutch data is from the social housing sector, while the Danish data contains data from the homeowner-occupied sector. These aspects are addressed more in depth in the discussion section. Nevertheless, both analyses indicate that approximately 50% of the variance is due to occupant behaviour, and the other 50% is due to physical characteristics. These results are different when compared to the results of Sonderegger. This is understandable if our hypothesis that **the amount of influence of the occupant on residential heating consumption is also dependent on the building characteristics of the house they live in** is true. To test this, the same analysis on different groups of the sample in the next sections is conducted. The results are discussed per building characteristic; and depending on data availability, the analyses are conducted on both the Dutch and Danish samples.

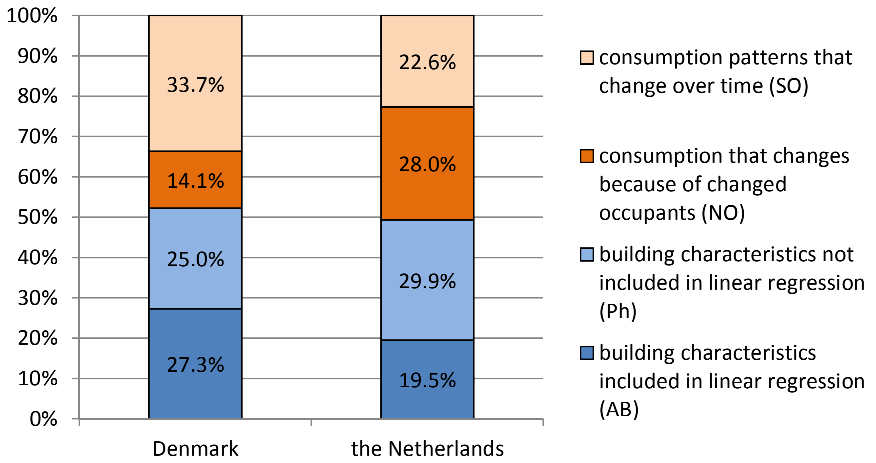

FIG. 4.2 Comparison influence building characteristics and occupants on variance energy consumption - Denmark and The Netherlands

4.5.2 Results per energy label

Executing the same analysis per energy label shows that occupants (changing heating consumption over time (SO) + changing heating consumption due to new occupants (NO)) have on average more influence percentage wise on the variance of energy-efficient houses than on energy-inefficient houses (Figure 4.3). This finding is in accordance with the assumptions in previous studies (e.g. [28]). However, this conclusion is only true if we compare dwellings with at least two label steps difference, e.g. the influence of the occupant is on average larger for a B Label dwelling than for an A Label dwelling. Further, it has to be taken into consideration that the variance of buildings with an energy-inefficient label is higher than the variance in energy-efficient buildings. This means that if one looks at the physical units, the influence of the occupant is higher for energy inefficient houses, but also the influence of building characteristics is higher for energy-inefficient houses (see appendix Figure 4.10 for results physical units).

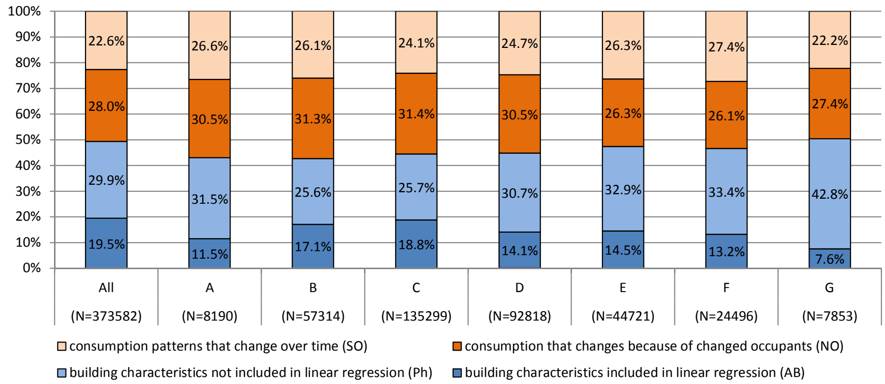

FIG. 4.3 Comparison of influence of building characteristics and occupants on variance energy consumption - Dutch data energy label

4.5.3 Results per construction year

An analysis of the construction year confirms our previous results in the analysis of the energy label. Figure 4.4 and Figure 4.5 indicate that in more recently built buildings (which are in most cases more energy-efficient than older buildings) a larger percentage of the variance is caused by occupants, while for older buildings the physical characteristics appear important for explaining the variance. However, especially for the Dutch case, this pattern is less clear than for the energy label results. A possible explanation is that very old buildings are more likely to be renovated than newer buildings. The construction period 1979-1998 forms an exception for both countries and shows a relatively low influence of the occupant. A possible explanation is that those buildings are not renovated yet, while buildings built before 1979 might be more frequently renovated and buildings built after 1999 were initially already built significantly more energy-efficient.

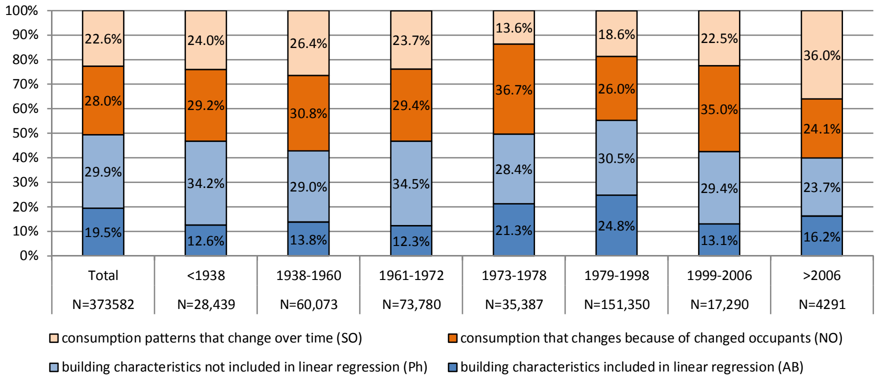

FIG. 4.4 Comparison of influence of building characteristics and occupants on variance energy consumption – construction year Dutch data

Figure 4.5 shows that the available building characteristics (AB) tend to capture a larger part of the variation in newer buildings, and physical characteristics (Ph) a smaller part. Especially in very new buildings, occupant behaviour seems important for explaining variations across the years.

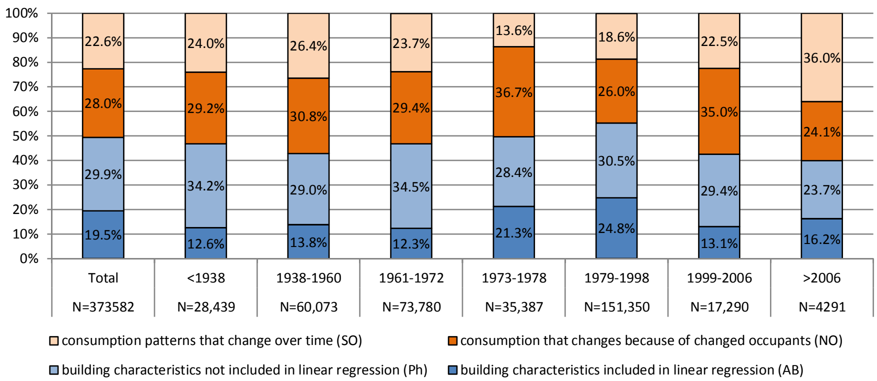

FIG. 4.5 Comparison of influence of building characteristics and occupants on variance energy consumption – construction year Danish data

4.5.4 Results per building type

Regarding the building type (building types defined in EPISCOPE are used[39]), Figure 4.6 indicates that occupants (changing heating consumption over time (SO) + changing heating consumption due to new occupants (NO)) explain a larger percentage of the variance for multi-family houses (common staircase with galleries, common staircase no gallery, maisonette) than for single-family houses (detached houses, semi-detached houses, end houses and terraced houses). Possible explanations for this could be that small changes in consumption patterns are more effective in multi-family houses than in single-family houses, because of the relatively smaller floor area of those dwellings. For example, opening a window in a small room will have more effect on thermal climate than opening a window of similar size in a larger room. This would also explain why the terraced houses do not show differences with the other multi-family houses, because from the single family houses they have, on average, the smallest floor area.

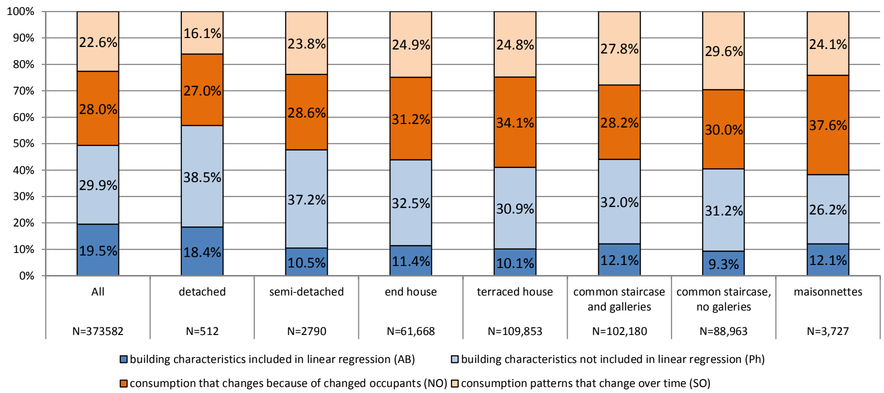

FIG. 4.6 Comparison of influence of building characteristics and occupants on variance energy consumption - Dutch data dwelling type

4.5.5 Results per type of ventilation system

The comparison of the three different ventilation systems in Figure 4.7 indicates that the influence of the occupant is larger for houses with a balanced ventilation system compared to houses with a natural or forced inlet mechanical exhaust ventilation system. This is expected, because houses with a balanced ventilation system often

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make use of heat recovery systems. To make optimal use of such a system, all air that enters and leaves the building should go through this system. However, occupants are still able to open windows. Opening the windows means the air does not pass the heat recovery system, which will lead to extra heat losses. Opening windows when a heat recovery system is installed will therefore have a larger effect than in houses where no heat recovery system is installed. Further, balanced ventilation systems are primarily installed in energy-efficient buildings. In Figure 4.3 it was already demonstrated that energy-efficient buildings are relatively more sensitive to occupant behaviour compared with energy-inefficient buildings.

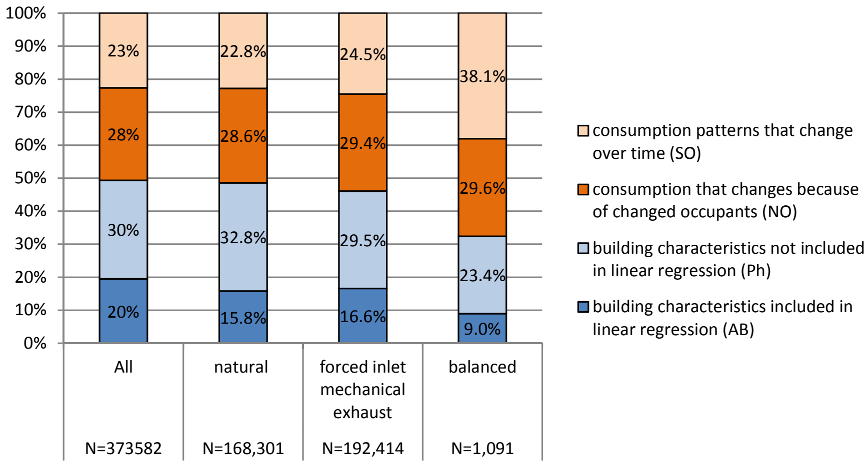

FIG. 4.7 Comparison of influence of building characteristics and occupants on variance energy consumption - Dutch data ventilation system

4.5.6 Results per type of heating system

Finally, the heating systems are compared. Because of the differences in the databases, the compared categories are different for the Dutch and Danish cases. For the Dutch case, different gas heating systems are compared. The results of the Dutch case (Figure 4.8) indicate (contrary to previous findings) that on average relatively energy-efficient installations are less sensitive to occupant behaviour than energy-inefficient systems. However, the most energy-efficient condensing boiler is an exception and the differences are relatively small, and therefore no conclusion can be drawn from this comparison. Furthermore, the figure shows that the consumption patterns that change over time (SO) are significantly higher for houses with a local heater (gas stove). One could expect that this is due to the relatively small sample of the local heater, however if we study the error of the variances the results seem still reliable (error of ±1%). This is interesting, because the operation of boiler systems are more or less the same, but the local gas heaters have a different operating system. Therefore, these results could indicate that different operation systems cause differences in behaviour.

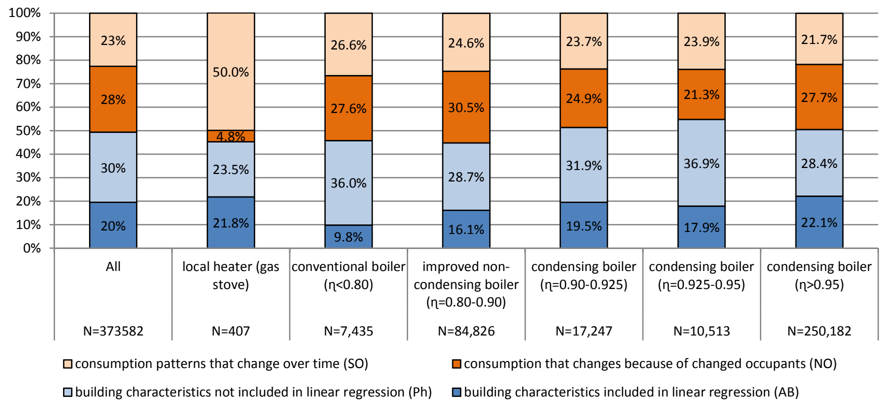

FIG. 4.8 Comparison of influence of building characteristics and occupants on variance energy consumption - Dutch data heating system

For the Danish case, a comparison was made between houses with gas heating and district heating systems. The results indicate, in particular, that the share of consumption that changes, because of changed occupants, is lower for houses with a district heating system compared to houses that are heated by gas.

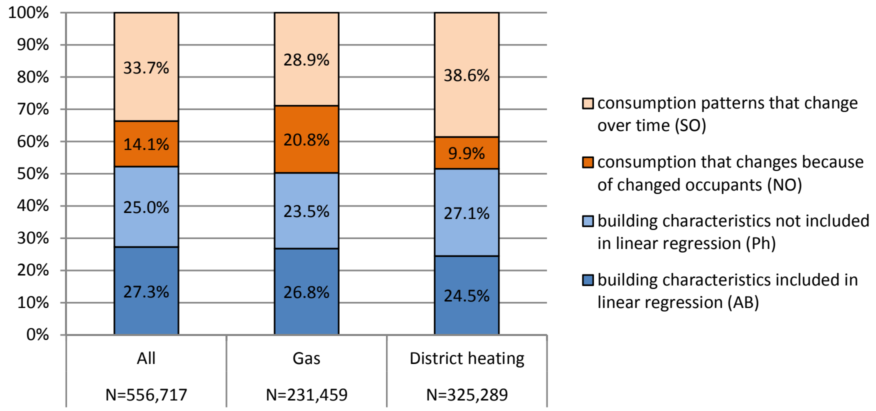

FIG. 4.9 Comparison of influence of building characteristics and occupants on variance energy consumption - Danish data heating system

4.6 Discussion

One of the main advantages of this study compared to previous studies is that this study could make use of two big datasets that included housing data over a six-year period. Using longitudinal data in residential heating consumption research presents significant potential for evaluating the effect of policy changes, newly installed technologies and renovations. Further, analyses on this topic have seldom been conducted based on two large datasets from two different countries (the Netherlands and Denmark).

There are some significant differences between the Dutch and the Danish datasets that should not be neglected. The most important difference is that the Dutch database contains multi- and single-family social rental houses, while the Danish dataset contains private detached houses. Several studies have shown that there is a difference between tenant and homeowner behaviour. Moreover, it could be expected that the building type would influence the results, because in multi-family housing one apartment can be heated from the other. This implies that the energy consumption in an apartment might also change when the neighbours change. This effect is not shown in the analysis separately. If this is the case, then the change due to change of neighbours is included in the change in occupant consumption patterns over time. Despite the differences, both databases indicated that occupants are responsible for half of the residential heating consumption and the building characteristics for the other half. Further, other values calculated from the datasets seemed to be remarkably close together. The difference might be reflected in the distribution of occupant consumption patterns. The results show that the percentage explained by moving occupants is relatively higher for the Dutch dataset (28%) compared to the Danish dataset (14.1%). This suggests that the consumption patterns of the moving Dutch occupants differ more from the consumption patterns of the previous occupants, compared to the Danish occupants. This could be due to house buyers exhibiting more similarities in consumption patterns with the previous owners, compared to new tenants with previous tenants. This could be the case because occupant characteristics of Dutch social housing tenants are very diverse, while the houses show more similarities and all have a low rental price compared to the owner-occupied housing stock.

One of the uncertainties in this study is the choice of using the data from 2010 and 2015. As Sonderegger [10] mentions in his study, it is expected that the variance in heating consumption among stayers increases over the years. However, it is expected that the variance will proportionally increase in time, because of the limited number of decisions that can be taken, the workings of peer pressure, and other 'stabilising influences'. In his paper, Sonderegger assumes that equilibrium will be achieved after six years, which supports our choice of years. However, he also states that his assumption awaits confirmation by further research. Accordingly, this is an uncertainty that should be taken into consideration.

4.7 Conclusions

This research investigated the influence of building characteristics and occupants on the variances in residential energy consumption. Therewith this study contributes to a better understanding of the energy performance gap and better interpretation of residential energy modelling and forecasting results. This is one of the first studies towards the influence of building characteristics and occupants on actual residential heating consumption on such a large scale with data from two different countries, which is seldom seen in the field.

This paper showed that variations in residential heating consumption across the years of Dutch social housing can be explained by occupants (49%), the Dutch energy simulation model (theoretical consumption) (20%), and by other physical characteristics that are not taken into account in the building simulation model (32%). For the Danish case, the results showed that 48% of the variation in residential heating consumption can be explained by occupants, 27% by the building characteristics mentioned in Table 4.2 and 25% by other physical characteristics. These results suggest that approximately half of the variation in residential heat can be ascribed to differences between buildings and approximately half of the variation to differences in occupant behaviour. These results were found by using an existing method (suggested by Sonderegger in 1978) with new and strongly improved data. This enabled comparisons of national contexts (The Netherlands and Denmark), of different types of heat supply (district heating and natural gas), different housing formats (social housing and private single-family houses), and different building types (detached and multi-family).

The results show that approximately half of the variance could be attributed to buildings and half to occupants. However, the follow-up analysis per building characteristic showed that the influences of the occupant are dependent on the building characteristics of the building. For example, the influence of occupants is larger for energy-efficient houses than for energy-inefficient houses. This is demonstrated in both comparisons of houses with different energy labels, and the analysis of houses built in a different period for the Dutch and the Danish cases. The results also show that the influence of occupants is dependent on the type of building installations in the house. For example, the occupant consumption patterns seem more important when the house has a local gas stove as a heating system than when the house has a gas boiler. Further, the influence of occupants is different, depending on the type of house.

The results of this research suggest that, on average, occupants significantly influence the variance in energy among buildings. Moreover, the magnitude of this influence is dependent on building characteristics, because some buildings are more sensitive to occupant consumption patterns than others. This is an important insight, because this indicates that building simulations will not be able to predict actual heating consumption correctly and accurately if occupant consumption patterns are considered. Although the results indicated that the influence of occupants is almost as important as the influence of building characteristics on residential heating consumption, thermal renovations will remain an important measure for reducing residential heating consumption. This is because deep thermal renovations (if correctly executed) usually result in an energy reduction for heating. Regarding occupant behaviour, more research is needed to determine the extent that occupant consumption patterns can be influenced to reduce residential energy consumption.

The results also indicate that there is still a relatively large number of physical characteristics that cause variance in heating consumption. More research is needed to determine the nature of these physical characteristics. If more is known about these parameters, they could be used to improve building simulation models. The high influence of occupants also suggests that it is not useful to aim for a perfect simulation model for one specific building, especially when the occupant behaviour is unknown. However, one can aim for a simulation model that shows the average heating consumption of a larger group of buildings.

This paper is one of the first studies to make use of large longitudinal databases in the field of residential heating consumption. It has already demonstrated the importance of this type of data for the field. Longitudinal databases that contain residential heating consumption data present significant potential for evaluating the effect of policy changes, newly installed technologies, and renovations.

Acknowledgements

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References

[1] EC, *EU energy in figures*, in *statistical pocketbook 2018*, E. Commission, Editor. 2018, EU Publications Office: Luxembourg. p. 268.

[2] Balaras, C.A., et al., *Empirical assessment of calculated and actual heating energy use in Hellenic residential buildings.* Applied Energy, 2016. **164**: p. 115-132.

[3] Menezes, A.C., et al., *Predicted vs. actual energy performance of non-domestic buildings: Using post-occupancy evaluation data to reduce the performance gap.* Applied Energy, 2012. **97**: p. 355-364.

[4] O'Neill, B.C. and B.S. Chen, *Demographic Determinants of Household Energy Use in the United States.* Population and Development Review, 2002. **28**: p. 53-88.

[5] Steemers, K. and G.Y. Yun, *Household energy consumption: a study of the role of occupants.* Building Research & Information, 2009. **37**(5-6): p. 625-637.

[6] Yohanis, Y.G., et al., *Real-life energy use in the UK: How occupancy and dwelling characteristics affect domestic electricity use.* Energy and Buildings, 2008. **40**(6): p. 1053-1059.

[7] Delzendeh, E., et al., *The impact of occupants' behaviours on building energy analysis: A research review.* Renewable and Sustainable Energy Reviews, 2017. **80**: p. 1061-1071.

[8] Gram-Hanssen, K., *Efficient technologies or user behaviour, which is the more important when reducing households' energy consumption?* Energy Efficiency, 2013. **6**(3): p. 447-457.

[9] Aydin, E., N. Kok and D. Brounen *The rebound effect in residential heating.* 2013. 33.

[10] Sonderegger, R.C., *Movers and stayers: The resident's contribution to variation across houses in energy consumption for space heating.* Energy and Buildings, 1978. **1**(3): p. 313-324.

[11] Guerra Santin, O., L. Itard and H. Visscher, *The effect of occupancy and building characteristics on energy use for space and water heating in Dutch residential stock.* Energy and Buildings, 2009. **41**(11): p. 1223-1232.

[12] Huebner, G.M., et al., *Explaining domestic energy consumption – The comparative contribution of building factors, socio-demographics, behaviours and attitudes.* Applied Energy, 2015. **159**(Supplement C): p. 589-600.

[13] Brounen, D., N. Kok and J.M. Quigley, *Residential energy use and conservation: Economics and demographics.* European Economic Review, 2012. **2012**(56): p. 931-945.

[14] Verhallen, T.M.M. and W.F.v. Raaij, *Household Behavior and the Use of Natural Gas for Home Heating.* journal of consumer research, 1981.

[15] Hansen, A.R., K. Gram-Hanssen and H.N. Knudsen, *How building design and technologies influence heat-related habits.* Building Research & Information, 2018. **46**(1): p. 83-98.

[16] Gill, Z.M., et al., *Low-energy dwellings: the contribution of behaviours to actual performance.* Building Research & Information, 2010. **38**(5): p. 491-508.

[17] Spataru, C., M. Gillott and M.R. Hall, *Domestic energy and occupancy: a novel post-occupancy evaluation study.* International Journal of Low-Carbon Technologies, 2010. **5**(3): p. 148-157.

[18] Guerra-Santin, O. and L. Itard, *Occupants' behaviour: determinants and effects on residential heating consumption.* Building Research & Information, 2010. **38**(3): p. 318-338.

[19] Hansen, A.R., *The social structure of heat consumption in Denmark: New interpretations from quantitative analysis.* Energy Research & Social Science, 2016. **11**(Supplement C): p. 109-118.

[20] Estiri, H., *Building and household X-factors and energy consumption at the residential sector: A structural equation analysis of the effects of household and building characteristics on the annual energy consumption of US residential buildings.* Energy Economics, 2014. **43**: p. 178-184.

[21] Chen, J., X. Wang and K. Steemers, *A statistical analysis of a residential energy consumption survey study in Hangzhou, China.* Energy and Buildings, 2013. **66**(0): p. 193-202.

[22] Druckman, A. and T. Jackson, *Household energy consumption in the UK: A highly geographically and socio-economically disaggregated model.* Energy Policy, 2008. **36**(8): p. 3167-3182.

[23] Jeeninga, H., M. Uyterlinde and J. Uitzinger, *Energieverbruik van energiezuinige woningen : effecten van gedrag en besparingsmaatregelen op de spreiding in en de hoogte van het reële energieverbruik.* ECN-C-01-072. 2001, [Petten]: Energieonderzoek Centrum Nederland.

[24] Kaza, N., *Understanding the spectrum of residential energy consumption: A quantile regression approach.* Energy Policy, 2010. **38**(11): p. 6574-6585.

[25] Vringer, K. and K. Blok, *The direct and indirect energy requirements of households in the Netherlands.* Energy Policy, 1995. **23**(10): p. 893-910.

[26] Alberini, A. and M. Filippini, *Response of residential electricity demand to price: The effect of measurement error.* Energy Economics, 2011. **33**(5): p. 889-895.

[27] Alberini, A., W. Gans and D. Velez-Lopez, *Residential consumption of gas and electricity in the U.S.: The role of prices and income.* Energy Economics, 2011. **33**(5): p. 870-881.

[28] Haas, R., H. Auer and P. Biermayr, *The impact of consumer behavior on residential energy demand for space heating.* Energy and Buildings, 1998. **27**(2): p. 195-205.

[29] Yu, Z., et al., *A systematic procedure to study the influence of occupant behavior on building energy consumption.* Energy and Buildings, 2011. **43**(6): p. 1409-1417.

[30] Belaïd, F., *Understanding the spectrum of domestic energy consumption: Empirical evidence from France.* Energy Policy, 2016. **92**(Supplement C): p. 220-233.

[31] ECN, energie-nederland and Netbeheer-nederland, *energietrends 2014*, in *energietrends.* 2014.

[32] Odyssee-Mure, *Netherlands | Energy Profile*, in *Energy efficiency trends and policies.* 2018, odyssee-muree.

[33] Fuentes, E., L. Arce and J. Salom, *A review of domestic hot water consumption profiles for application in systems and buildings energy performance analysis.* Renewable and Sustainable Energy Reviews, 2018. **81**: p. 1530-1547.

[34] Hansen, A.R., *'Sticky' energy practices: The impact of childhood and early adulthood experience on later energy consumption practices.* Energy Research & Social Science, 2018. **46**: p. 125-139.

[35] Strengers, Y. and C. Maller, *Adapting to 'extreme' weather: mobile practice memories of keeping warm and cool as a climate change adaptation strategy*. Environment and Planning A: Economy and Space, 2017. **49**(6): p. 1432-1450.

[36] Gram-Hanssen, K., *Understanding change and continuity in residential energy consumption.* Journal of Consumer Culture, 2011. **11**(1): p. 61-78.

[37] Rinkinen, J. and M. Jalas, *Moving home: houses, new occupants and the formation of heating practices.* Building Research & Information, 2017. **45**(3): p. 293-302.

[38] ISSO, *Energieprestatie advies woningen*, in *82.3*, ISSO, Editor. 2011: Rotterdam.

[39] Filippidou, F. and N.E.T. Nieboer. *Residential Building Typology.* EPISCOPE 2013 2013 [cited 2019 20-3-2019]; classification scheme for residential buildings --- construction year classes --- pictures of example buildings]. Available from: http://episcope.eu/building-typology/country/nl/.

Appendix

TABLE 4.7 Linear regression results of the Dutch sample year 2010 and 2015 (AB)

Model	Unstandardized coefficients 2010		t	Sig.
	B	Std. Error		
Constant	27,224.01	79.84	341.07	<0.01
Theoretical gas consumption [MJ]	19.03	0.0070	314.022	<0.01

* *R^2 0.210, dependent variable gas consumption 2010*

Model	Unstandardized coefficients 2015		t	Sig.
	B	Std. Error		
Constant	28,246.89	83.88	803.153	<0.01
Theoretical gas consumption[MJ]	19.24	0.07	0.517	<0.01

* *R^2 0.180, dependent variable adjusted gas consumption 2015*

(AB) Average explanation of available building characteristics is (0.217+0.186)/2 = 0.2015 = 20.15%

TABLE 4.8 Linear regression results of the Danish sample year 2010 and 2015

Model	Unstandardized coefficients 2010		t	Sig.
	B	Std. Error		
Constant	-37,990.73	240.366	-158.05	<0.01

** R^2 0.2860, dependent variable gas consumption 2010*

Model	Unstandardized coefficients 2015		t	Sig.
	B	Std. Error		
Constant	-38,546.99	241.192	-159.82	<0.01

** R^2 0.2595, dependent variable adjusted gas consumption 2015*

(AB) Average explanation of available building characteristics is (0.286+0.2595)/2 = 0.27275 = 27.28%

TABLE 4.9 Coefficients per parameter of the linear regression of the Danish sample year 2010 and 2015

Model	heat2010		adjheat2015	
	Coef.	SE	Coef.	SE
Area (logarithmic transformed)	11,420.611***	55.956	11,757.833***	56.149
Gas (1=Yes)	3.727,314***	18.492	1,024.326***	18.556
Number of rooms	173.442***	10.298	212.825***	10.333
Wood-stove (1=Yes)	-1,316.447***	23.932	-1,329.944***	24.015
Attic floor (1=Yes)	-715.892***	27.752	-944.257***	27.847
Basement (1=Yes)	3,025.429***	24.130	3,344.441***	24.213
Building period (ref. “Before 1938”)				
1938-1960	-508.627***	34.381	-587.511***	34.499
1961-1972	-1,737.207***	36.120	-1,859.880***	36.244
1973-1978	-2,954.989***	40.084	-3,170.666***	40.222
1979-1998	-5,149.254***	43.136	-5,040.772***	43.284
1999-2006	-5,937.958***	53.440	-6,018.504***	53.624
After 2006	-7,816.063***	66.363	-8,027.991***	66.591
Roof material (Ref. “Fibercement”)				
Cement stone	346.156***	29.141	19.578	29.241
Tile	1,204.509***	25.175	1,068.295***	25.262
Other material	1,513.594***	35.536	1,609.229***	35.658
Exterior wall material (Ref. “Bricks”)				
Wood	-1,963.962***	71.393	-1,480.936***	71.638
Concrete	364.676***	46.569	329.333***	46.729
Other material	-565.596***	91.204	-503.470***	91.517
Constant	-37,990.729***	240.366	-38,546.992***	241.192
R^2	0.286		0.260	
Number of observations	512,393		512,393	

**** $p<0.01$, ** $p<0.05$, * $p<0.1$*

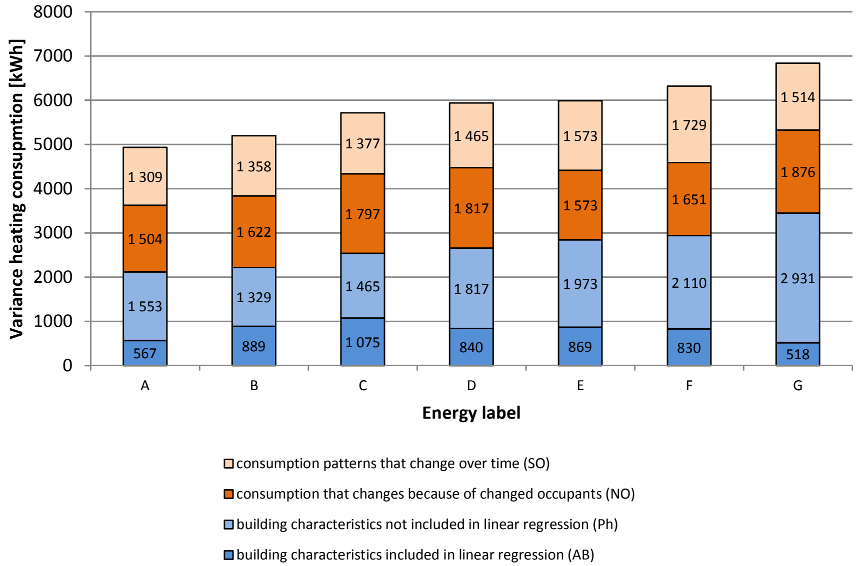

FIG. 4.10 Comparison of influence of building characteristics and occupants on variance energy consumption using physical units instead of percentages - Dutch data energy label

5 Calibration of Energy Simulation Models on a Building Stock Level using Actual Energy Consumption Data

Making Building Energy Simulations a more Reliable Tool for Policymakers

Submitted for publication as: van den Brom, P., Itard, L., & Visscher, H. (2020). Automated calibration of energy simulation models on a building stock level using actual energy consumption data.,

The previous chapters demonstrated that both, technical characteristics and residents play a role in the Energy Performance Gap. They also showed that residential energy consumption differs widely among households. This implies that predicting energy consumption for an individual building, without knowing the exact behaviour of the occupant, will almost never be accurate for individual cases. However, the conclusion of Chapter 4 suggests that, although predicting energy consumption on an individual level is impossible without specific occupant and building information, the average energy consumption of a building should be able to be predicted fairly precisely. Therefore, this chapter

investigates whether the average Energy Performance Gap can be reduced by changing the assumptions that are used in building simulation models. To see if the assumptions can be improved to reduce the Energy Performance Gap, 313 dwellings are simulated, and the results are compared to actual energy consumption. After this, a calibration on building stock level is carried out using actual data with the aim that the theoretical model can learn from real energy consumption data.

ABSTRACT

Building energy simulation models are an important tool, not only in building design but also for policy making. Previous research has shown that there is a significant gap between actual energy consumption, and the energy consumption calculated by building energy simulation models. Many researchers, practitioners, and policymakers mainly impute this energy performance gap to occupant behaviour. One would expect this gap to be less at building stock level because occupant behaviour would be averaged. However, the performance gap is known to be high at a building stock level too, indicating a more structural problem in building energy simulation models. Being able to assess and predict correctly energy use in the building stock is essential to realize national and international energy saving targets. As actual energy consumption data at individual house level are becoming more often available or are registered by national bodies, this research introduces a method that uses actual energy consumption data and automatic calibration techniques to improve assumptions in building energy simulation models used to assess the whole building stock. Two types of models were tested; the first one being the steady state model used in NL in the framework of the EPBD, the other one being a dynamic model in EnergyPlus. The method was able to reduce the root mean square error of the energy performance gap by nearly 24% for the steady state simulation method, and by 27% for the dynamic simulation method, and, most important, the average energy performance gap in the sample (133 dwellings) as well as in the control group (180), disappeared almost completely. This method has the potential to make building simulation models a more reliable tool for policymakers.

KEYWORDS

Energy performance gap, actual energy consumption, calibration, reliable decision tool

Nomenclature

acc	=	accumulated intensity of solar radiation on a vertical plane on the south	[MJ/m^2]
$A_{catg,i}$	=	floor area category house *i*	[-]
$A_{fac,i}$	=	area façade	[m^2]
A_g	=	floor area	[m^2]
$A_{g,i}$	=	floor area house *i*	[m^2]
A_j	=	area daylight opening including window frame area	[m2]
B	=	presence of bathtub	[-]
C_b	=	standard domestic hot water use per bathtube	41.5 [l/day]
C_{conv}	=	conversion factor	68.734 [MJ day/l year]
C_d	=	standard domestic hot water use per shower visit	20.8 [l/day]
C_k	=	standard domestic hot water use in kitchen	13.03 [l/day]
C_p	=	standard domestic hot water use per person	7.1 [l/day]
C_w	=	standard domestic hot water use sink	3.97 [l/day]
D	=	presence of shower	[-]
$f2$	=	factor for the part of airtightness related characteristic air tightness	[-]
GGF_i	=	family factor per house *i*	[-]
i	=	house number	[-]
$\eta_{b,i}$	=	utilization factor of the heat gain	[-]
η_{heat}	=	system efficieny of heating system	[-]
η_{spec}	=	specific efficiency	[-]
$\eta_{sys,i}$	=	system efficiency of room heating installation	[-]
P_i	=	number of family members per house *i*	[-]
$Q_{act,i}$	=	actual energy use house *i*	[MJ/year]
$Q_{demand,i}$	=	theoretical energy demand house *i*	[MJ/year]
$Q_{dhw,i}$	=	theoretical energy use for domestic hot water in house *i*	[MJ/year]
$Q_{heat,i}$	=	theoretical energy use for heating in house *i*	[MJ/year]
$Q_{gain,i}$	=	theoretical heat gains house *i*	[MJ/year]
$Q_{hbruto,i}$	=	gross heat demand for house *i*	[MJ/year]
$Q_{heat,i}$	=	heat generation efficiency	[-]
$q_{inf,10i}$	=	air tightness of house *i*	[dm^3/s]
$Q_{infil,i}$	=	heat loss due to infiltration of house *i*	[MJ/year]
$Q_{intern,i}$	=	heat gain due to internal heat production in house *i*	[MJ/year]
Q_{intern}	=	internal heat production per m2 usable floor area	[W/m^2]
$Q_{loss,i}$	=	total heat loss of house *i*	[MJ/year]
$Q_{pilotflame,i}$	=	energy use pilot flame heating installation of house *i*	[MJ/year]
$Q_{sol,i}$	=	heat gain due solar radiation of house *i*	[MJ/year]
$Q_{stilstandsv}$	=	standby losses of domestic hot water system	[MJ/year]
$Q_{theo,i}$	=	total theoretical energy use of house *i*	[MJ/year]
$Q_{trans,i}$	=	heat loss due to transmission of house *i*	[MJ/year]
$Q_{vent,i}$	=	heat loss due to ventilation	[MJ/year]
$R_{cj,i}$	=	Thermal resistance	[m^{2}K/W]
$RMSE$	=	Root Mean Square Error	[MJ/year]
T_e	=	outdoor temperature	[K]
t_{hp}	=	duration heating season	18,3168 [Ms]
T_i	=	indoor temperature	[K]
t_{stook}	=	duration heating season	[Ms]
$U_{glass,i}$	=	Thermal transmittance of glass of house *i*	[W/m^{2}K]
$z.rs$	=	orientation and shading reduction coefficient of daylight opening*	[-]
ZTA	=	solar heat gain factor	[-]
α_i	=	heat resistance of the air layer on the inner side of the construction	0.13 [m^{2}K/W]
α_o	=	heat resistance of the air layer on the outer side of the construction	0.04 [m^{2}K/W]
c	=	heat capacity air	1000 [J/kgK]
ρ	=	air tightness air	1.2 [kg/m^3]

5.1 Introduction.

Reducing residential energy consumption is currently high on the political agenda of many national and municipal governments. Household final energy consumption is estimated to be responsible for approximately 25% of the total energy consumption in Europe [1]. Building energy simulations are frequently used to make informed decisions in the design process, to calculate payback times, and to decide which renovation measure would result in the highest energy saving at acceptable costs. Simulation results are not only used at an individual building level, but also at a building stock level. For example, policymakers use the results of building energy simulation models at a housing stock level to determine which and how many renovation measures have to be taken to achieve the energy saving goals that are set, and to evaluate the requirements for existing or new energy supplies at regional or national levels [2]. Municipalities and housing associations use such models to decide on what neighbourhoods or building blocks to target in renovation programs.

Although building energy simulation results are widely used for decision-making, several studies have shown that there is a large gap between simulation results and actual energy consumption or savings [3-9]. The gap between simulated and actual energy consumption is often referred to as the energy performance gap (EPG). As a consequence of this gap, energy saving targets and payback times are often not achieved [10-12].

Many studies have already investigated the EPG and found relationships between energy consumption and both occupant and building characteristics [13]. These relationships often have both direct and indirect influences on residential energy consumption [14]. The high number of input variables that are needed for building energy simulation models, the interaction of these variables, the unpredictability of occupant behaviour, and climate conditions make residential energy consumption complex to predict. In fact, the results of previous studies show that every house and every resident is unique in their energy consumption. Based on the previous research findings it is fair to conclude that it is impossible to predict energy consumption accurately at an individual level when the assumptions for occupant behaviour remain constant for every building (e.g. temperature set points and ventilation rates) [15]. In addition to occupant behaviour and building characteristics, oversimplification of simulation models, mistakes in the construction process, wrong inputs, and assumptions in the simulation models also contribute to the EPG.

Further, a significant average EPG is detected at the dwelling stock level, which is clearly shown in Figure 5.1. This figure presents the average difference between actual and theoretical energy consumption per energy label (Energy Performance Certificate) of dwellings in the Netherlands [16]. For policymakers, the average energy consumption of building stock, or a specific group of buildings, is more important than the energy consumption of individual dwellings, because policy targets are based on these aggregated dwellings. This is also stimulated by the Energy Performance Building Directive (EPBD), which requires every member state to provide a roadmap with measurements at a national level to achieve the required reduction of CO_2 emissions [17]. In addition, also other organisations (apart from the government) use building simulation results for policymaking. For example, the Dutch social housing associations signed an agreement that they would reduce the energy consumption of their housing stock by 33% by 2021, compared to their use in 2008. This target has to be reached by renovating the buildings up to an average energy label of B. However, Figure 5.1 shows that on average, energy efficient buildings (labels A–B) consume more energy than expected, while energy inefficient buildings (labels D–G) consume less energy than expected. Consequently, less energy will be saved than expected in reality because the targets were set based on simulated energy and not on the actual energy. This example shows that steering with inaccurate models will reduce the probability of achieving the aimed energy saving goals. This is also confirmed by the research of Filippidou et al. [18].

Despite these drawbacks, building energy simulation models are currently the best tool available. However, for these simulations to become a more effective tool, it is important that they predict actual energy consumption fairly accurately. On an individual level, calibration methods are often used to reduce the EPG [19]. Assumed values such as temperature settings, and ventilation and infiltration rates, are adapted so that the simulation results match the detailed measured energy consumption data. If the gap for the baseline model is reduced, it is more likely that the estimates of energy saving measures will be reliable [20]. This implies that the payback times of renovation measures can be more accurately estimated, which means the consultant has more information to determine the most optimal renovation to reduce energy consumption as much as possible.

Differences in occupant behaviour are often mentioned as the most important cause of EPGs [21]. However, Figure 5.1 shows that there is also a gap in the average energy consumption per energy label. If differences in occupant behaviour are the most important cause of the gap, it is expected that the differences in behaviour would be equalised for the average consumption. However, Figure 5.1 shows this is not the case. This indicates that there is probably a more structural problem than only differences in occupant behaviour. To reduce the average EPG calibration on an individual level, using high frequency measured energy data (e.g. hourly data or lower), is not a solution because this type of calibration would result in overfitting outcomes for one specific dwelling and not provide information to reduce the EPG on a building stock level and it would be too time consuming. Up to now calibration procedures only take place on individual building level. This means that on building stock level, the level on which policymakers often work, the models are not calibrated and therefore not reliable.

In this research we propose a method to reduce the EPG on a building stock level. The method is based on a traditional calibration method but doesn't require high frequency energy data of dwellings; instead it requires annual actual energy data of individual dwellings which is more widely available. To prevent overfitting energy data of multiple dwellings is required that together form a representative sample of the building stock. The starting point of the method is that every simulation model makes use of assumptions; for example for energy related occupant behaviour (such as temperature settings or ventilation rate); sometimes also assumptions are made for building characteristics that cannot be identified by visual inspections like façade insulation [22]. The hypothesis is that if the assumptions in building simulation models are more carefully chosen, the average EPG will be smaller and the building energy simulation models will become an even more useful tool for policymakers. The proposed method to reduce the gap does not change the calculation method, but aims to make different assumptions for the simulation models to allow more accurate predictions. This is achieved by using actual yearly energy consumption data for each individual dwelling, similar as a traditional calibration procedure. An optimisation algorithm calibrates the model by changing the assumptions in order to reduce the average squared difference between actual and theoretical energy consumption at building stock level looking at the average consumption in the group/stock. One could say that the simulation model "learns" from the actual energy consumption data. The proposed method is demonstrated by using a sample of 133 dwellings from the Dutch national housing energy survey: 'WoON module energie 2012' [23]. The effectiveness of the method is tested by a control group of 180 dwellings. Further, the method is tested for a steady state simulation model as well as a dynamic simulation model. Those two different methods are tested because the steady state is frequently used in practice and one could assume that the EPG is (partly) caused by using a steady state instead of a dynamic situation. The assumptions in these models are based on the standard values set in ISSO 82.3, which is used for the Dutch energy label calculation method.

This paper is structured as follows: First, the two building energy simulation (BES) models that are used in this research and the standard values as set in ISSO 82.3 are explained. Second, the dataset we use for the optimisation is described, followed by an explanation on the method. The results are then described and explained in the results section. The advantages, disadvantages, and points of attention of the method are discussed in the discussion section. Finally, conclusions are drawn and recommendations are made for further research.

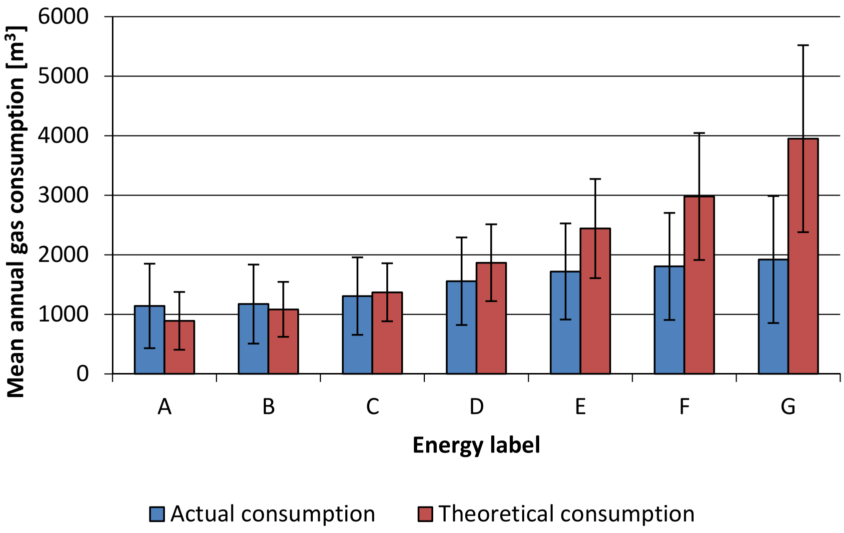

FIG. 5.1 Actual and theoretical gas per m² of dwellings consumption per energy label (Majcen et al., 2013) [4]

TOC

5.2 Description of the BES models

The method is demonstrated on two types of models, a steady state and a dynamic BES model. In this section both methods are explained. .

5.2.1 Steady state model: the Dutch energy labelling method

Like to all European countries, Dutch buildings are required to have an energy certificate if they are rented out or sold. In the Netherlands, this certificate is referred to as the energy label. The energy label of a building is determined by the Energy Index, which is based on the calculated energy consumption of a building. The calculation method for the Dutch energy label and Energy Index is based on the building characteristics of the building, which can be found in ISSO 82.3 and 82.1 [24]. It is a static yearly calculation method based on energy balances (see also description below). This method is also used by the national government, housing associations and municipalities to set targets at stock level and monitor the advances of specific building stocks. For instance the energy labels are stored in a national data base to track the energy performance of the housing stock and to assign subsidies for energy renovations; the housing associations use their own database (SHAERE) to track the energy efficiency of their housing stock and to define policies and targets.

Description of Steady state BES model

Due to our cleaning process and selection of cases (see Section 5.3) some aspects described in ISSO 82.3 were not applicable to our dataset [24]. For example, our dataset did not contain dwellings with heat recovery in the shower, quality declarations of certain building installations, solar energy, boilers outside the thermal envelope, heat pumps, circulation pipes, secondary heating, or domestic hot water systems. Further, all dwellings in the sample had a high temperature space heating system (>55 °C) and none of the dwellings has a glass enclosed patio. Therefore, the method we describe below is a simplified version of both ISSO 82.1 and 82.3 (publication year 2011).

In the method for this study, we used theoretical energy consumption, which is a combination of energy use for domestic hot water and heating (Eq 5.1).

$$Q_{theo,i} = Q_{dhw,i} + Q_{heat,i}$$

EQUATION 5.1

$Q_{theo,i}$ = total theoretical energy use of house *i* [MJ/year]
$Q_{dhw,i}$ = theoretical energy use for domestic hot water in house *i* [MJ/year]
$Q_{heat,i}$ = theoretical energy use for heating in house *i* [MJ/year]

The amount of energy used for domestic hot water is based on the amount of domestic hot water used and the efficiency of the heating system. The amount of domestic hot water used is based on the number of occupants in the house, which in turn is based on four different floor area categories. Apart from the number of occupants, the presence of a shower or bath will influence the amount of domestic hot water usage. All of this together forms the amount of used domestic hot water, which is represented by Eq 5.2.

$$Q_{dhw,i} = \left\{ C_{conv} \left[(C_k \cdot GGF_i + C_w \cdot GGF_i + C_p \cdot P_i + C_d \cdot P_i + C_p \cdot P_i + C_b \cdot B \cdot P_i) \cdot \boldsymbol{A_{catg,i}} \right] \cdot \frac{1}{\eta_{spec}} \right\} + Q_{stilstandsv}$$

EQUATION 5.2

$Q_{dhw,i}$ = theoretical energy use for domestic hot water in house *i* [MJ/year]
C_{conv} = conversion factor 68,734 [MJ day/l year]
C_k = standard domestic hot water use kitchen 13.03 [l/day]
GGF_i = family factor per house *i* [-]
C_p = standard domestic hot water use per person 7.1 [l/day]
C_d = standard domestic hot water use per shower visit 20.8 [l/day]
D = presence of shower [-]
P_i = number of family members per house *i* [-]
C_b = standard domestic hot water use per bath 41.5 [l/day]
B_i = presence of a bathtub in house *i* [-]
P_i = number of family members per house *i* [-]
$A_{catg,i}$ = floor area category in house *i* [-]
η_{spec} = specific heat efficiency [-]
$Q_{stilstandv}$ = standby losses of domestic hot water system [MJ/year]

Energy use for heating can be seen as a balanced system. Due to transmission, ventilation, and infiltration, a building loses heat (Eq 5.6) and due to solar radiation, internal heating loads, and the heating system, a building gains heat (Eqs 5.9-5.11). If a constant temperature is assumed (which is the case in this method) the gains and losses should be in balance. Because the amount of energy provided by the heating system to the room is not equal to the amount of energy the system needs, the efficiency of the heating system should also be taken into account (Eqs 5.3-5.5). The efficiency of the systems is dependent on the type of boiler.

$$Q_{heat,i} = \frac{Q_{hbruto,\mathrm{i}}}{(\eta_{heat})} + Q_{pilotflame,i}$$

EQUATION 5.3

$$Q_{hbruto,\mathrm{i}} = \frac{Q_{demand}}{\eta_{sys,i}}$$

EQUATION 5.4

$$Q_{demand,\mathrm{i}} = Q_{loss,i} - \eta_{b,i} \cdot Q_{gain,i}$$

EQUATION 5.5

$$Q_{loss,i} = Q_{trans,i} + Q_{air,i}$$

EQUATION 5.6

$Q_{heat,i}$ = theoretical energy use for heating in house *i* [MJ/year]
$Q_{hbruto,\ i}$ = gross heat demand for house *i* [MJ/year]
η_{heat} = system efficiency of heating system *i* [-]
$Q_{demand,i}$ = theoretical energy demand in house *i* [MJ/year]
$\eta_{sys,i}$ = system efficiency of room heating installation in house *i* [-]
$Q_{loss,i}$ = total heat loss of house *i* [MJ/year]
$\eta_{b,i}$ = utilization factor of the heat gain in house *i* [-]
$Q_{gain,i}$ = theoretical heat gains in house *i* [MJ/year]
$Q_{trans,i}$ = transmission losses of house *i* [MJ/year]
$Q_{air,i}$ = ventilation and infiltration losses of house *i* [MJ/year]

Transmission losses are dependent on the façade area, Rc value of the facade, glass area, U value of the windows, and difference between indoor and outdoor temperature (Eq 5.7).

$$Q_{trans,i} = [A_{fac,i} \cdot \left(\frac{1}{\alpha i} + R_{cj,i} + \frac{1}{\alpha o}\right)^{-1} + \left(A_i \cdot U_{glass,i}\right)] \cdot (\boldsymbol{T_i} \cdot \text{-}T_e) \cdot t_{hp}$$

EQUATION 5.7

$Q_{trans,i}$ = transmission losses of house *i* [MJ/year]
$A_{fac,i}$ = façade area of house house *i* [m^2]
α_i = heat resistance of the air layer on the inner side of the construction 0.13 [m^2K/W]
$R_{cj,i}$ = thermal resistance facade of house *i* [m^2 K/W]
α_o = heat resistance of the air layer on the outer side of the construction 0.04 [m^2K/W]
A_i = glass area of house house *i* [m^2]
T_i = indoor temperature [K]
T_e = outdoor temperature [K]

t_{hp} = duration heating season 18,3168 [Ms]

The heat loss due to air change is described in Eq 5.8. The ventilation rate is dependent on type of ventilation system. Infiltration is dependent on floor area and building type. Our sample contained only one dwelling type, and the infiltration rate was therefore the same per m^2 for each building.

$$Q_{air,i} = \rho c(\boldsymbol{q}_{\boldsymbol{v}_{i,i}} \cdot \mathrm{Ag}\ ) \cdot (\boldsymbol{T_i}\text{-}T_e) \cdot t_{hp+}\ \rho c \cdot (f_2 \cdot \boldsymbol{q}_{\boldsymbol{inf},\mathbf{10}_i} \cdot Ag\ ) \cdot (\boldsymbol{T_i}\text{-}T_e) \cdot t_{hp}$$

EQUATION 5.8

$Q_{air,i}$ = ventilation and infiltration losses of house *i* [MJ/year]
ρ= air tightness air 1.2 [kg/m^3]
c = heat capacity air 1000 [J/kgK]
$q_{vj,i}$ = factor for air tightness related to floor area of house *i* [$dm^3/s.m^2$]
T_i = indoor temperature [K]
T_e = outdoor temperature [K]
t_{hp} = duration heating season 18,3168 [Ms]
f_2 = factor for the part of airtightness related characteristic air tightness [-]
$q_{inf,10i}$ = airtightness of house *i* [dm^3/s]

In addition to the heating system, the building gains heat by internal heat gains and solar radiation (Eqs. 5.9-5.11).

$$Q_{gain,\mathrm{i}} = Q_{intern,i} + Q_{sol,i}$$ EQUATION 5.9

$Q_{gain,i}$ = theoretical heat gains in house *i* [MJ/year]
$Q_{intern,i}$ = heat gain due to internal heat production in house *i* [MJ/year]
$Q_{sol,i}$ = heat gain due to solar radiation in house *i* [MJ/year]

$$Q_{intern,i} = Q_{\mathrm{intern}} \cdot t_{stook} \cdot A_{g,i}$$ EQUATION 5.10

$Q_{intern,i}$ = heat gain due to internal heat production in house *i* [MJ/year]
Q_{intern} = internal heat production per m^2 usable floor area [W/m^2]
t_{stook} = duration heating season 18,3168 [Ms]
$A_{g,i}$ = floor area house *i* [m^2]

$$Q_{sol,i} = (A_i \cdot ZTA_i \cdot \mathrm{z.rs}) \cdot acc$$ EQUATION 5.11

$Q_{sol,i}$ = heat gain due to solar radiation in house *i* [MJ/year]
A_i = glass area of house house *i* [m^2]
ZTA_i = solar heat gain factor of house *i* [-]
z.rs = orientation and shading reduction coefficient of daylight opening [-]
acc= accumulated intensity of solar radiation on a vertical plane on the south [MJ/m^2]

Assumptions in the Dutch energy labelling method

The energy labelling method is primarily meant to provide a quick and understandable insight into the energy efficiency state of existing buildings. Because the building characteristics documentation of existing buildings is often not up to date (or not available), the building characteristics have to be gathered by visual inspections. However, it is for financial (keeping the inspection costs low) and technical reasons not always possible to determine all the building characteristics required by visual inspections alone. Therefore, the ISSO 82.3 method provides standard values that can be used if the required data are not available. Apart from building characteristics, standard values for energy related occupant behaviour are also provided. Table 5.1 presents descriptions of how the assumptions for building characteristics and occupant behaviour are made, and on which characteristics they are dependent. The values are dependent on different characteristics of the building e.g. the Rc values are dependent on construction year, the ventilation rates are dependent on the type of ventilation system and the amount of domestic hot water is dependent on the floor area category the dwelling belongs to..

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TABLE 5.1 Assumptions according to ISSO 82.3

Category	Assumptions
Façade insulation (Rc, [m²K/W])	If the insulation is unknown and cannot be measured the assumed insulation level is based on construction year. ISSO 82.3 assumes the following values Built before 1965 = 0.19 Built between 1965-1975 = 0.43 Built between 1975 – 1988 = 1.3 Built between 1988 – 1992 = 2 Built after 1992 = 2.3
Floor insulation (Rc, [m²K/W])	If the insulation is unknown and cannot be measured the assumed insulation level is based on construction year. ISSO 82.3 assumes the following values Built before 1965 = 0.15 Built between 1965-1975 = 0.17 Built between 1975 – 1983= 0.52 Built between 1983 – 1992 = 1.3 Built after 1992 = 2.53
Roof insulation(Rc, [m²K/W])	If the insulation is unknown and cannot be measured the assumed insulation level is based on construction year. ISSO 82.3 assumes the following values Built before 1965 = 0.22 Built between 1965-1975 = 0.86 Built between 1975 – 1988 =1.3 Built between 1988 – 1992 = 2 Built after 1992 = 2.53
Ventilation rate	Assumed ventilation rate is based on type of ventilation system (natural ventilation, mechanical exhaust ventilation, demand based mechanical exhaust ventilation, balanced ventilation with heat recovery) and minimum ventilation rate per m^2 floor area. natural ventilation $q_{vnat,i}$ =0.47; mechanical exhaust ventilation $q_{vmech,i}$=0,47; demand based ventilation $q_{db,i}$=0,29; balanced ventilation $q_{vbal,i}$=0,47. If a heat recovery system is present $q_{v,j,i}$ is multiplied by 1- efficiency of heat recovery system
Infiltration rate	Assumed infiltration rate is based on floor area and type of building (detached dwelling, semidetached dwelling, terraced house, common staircase and galleries, common staircase no galleries and maisonettes) f_{2i}= air permeable factor based on ventilation system (0.12 for demand based else 0.13); The exact values of $q_{inf,10i}$ can be found in table 14 of ISSO 82.3 (2011).
Indoor temperature	Assumed average constant indoor temperature of 18°C (building is considered as being one zone; the average is based on heated floor area)
Domestic hot water consumption	Assumed amount of domestic hot water is based on number of occupants, which is based on floor area. Further it takes into account if a shower or bath and/or dishwasher is/are present and if water saving shower heads are installed. Eq 5.2
Efficiency of heating system	The assumed efficiency of the heating system is based on the type of system, but also if the system is placed outside or within the thermal envelope of the building. The exact values can be found in table 19 of ISSO 82.3 (2011).
Efficiency of domestic hot water system	The assumed efficiency of the heating system is based on the type of system, but also if the system is placed outside or within the thermal envelope of the building. The exact values can be found in table 24 of ISSO 82.3 (2011).

5.2.2 Dynamic BES model

In addition to the steady state BES the method is also tested on a dynamic BES method. In the steady state simulations stationary conditions are assumed, and average values of environmental temperatures and for solar radiation are used. Because the process is in reality more complex, dynamic simulation methods are developed. The dynamic simulation models should be able to show a more realistic representation of reality, because they also take dynamic effects into account, such as the properties of the structures and the effects of climatic variations over time.

For this case study, we used EnergyPlus software to make dynamic BESs at individual building level. First, the input file was created using DesignBuilder, which is a graphical user interface that uses EnergyPlus to calculate building energy consumption [25]. The basic simulation file is a simple square-shaped building with windows on two sides of the building, a gas boiler, a gas domestic hot water system, and a mechanical exhaust ventilation system. The simplified geometry is used because the used database did not contain information about the orientation of windows and facades. The partition walls between dwellings are modelled as a wall with a very high insulation rate (Rc = 10 m2k/W). This was also done for the roofs or floors of the apartments, because we assumed that they were not exposed to the outdoor environment. This is because our sample contains only apartments in the middle of a building block, i.e. surrounded at both sides, below and above by other identical apartments (sees section 5.3.1). The other assumptions that had to be taken are the same as the assumptions described in the steady state BES method.

5.3 Data

This section provides a description of the database, the validity of the models that we used, a description of the sample which we use to demonstrate the proposed method and a description of the control group which we use to demonstrate the effectiveness of the method.

5.3.1 Description database

The database used for this research is the WoON energy module database from 2012, which is currently the most recent available dataset containing both actual and theoretical energy consumption. The WoON energy module 2012 provides a representative sample of the energy performance of houses in the Netherlands in 2012. The dataset contains the following information for each individual dwelling: building type, floor area, type of heating system, type of domestic hot water system, construction year, insulation rates of floor roof and facades (assumed based on construction year or measured by thickness) ventilation system, theoretical yearly gas and/or electricity consumption, and actual gas and/or electricity consumptions for each year of the period 2004–2010. The dataset contains 4,800 cases. The actual gas consumption data are available as standard yearly consumption, meaning that the measured annual consumption was standardized according to annual degree days before being stored in the WoON database. For this research the standardized energy consumption was converted back to actual annual consumption of the considered year by correcting back for the degree days of that year.

Building characteristics data were gathered by visual inspections. However, if it was not possible to determine the characteristics from a specific building component, assumptions were made as described in Table 5.1, which are the standard values that we will optimise.

Approximately 95% of Dutch households use gas as a heating source [26]. In countries such as the Netherlands, energy for heating constitutes the main energy demand of a house. Further, energy consumption for heating has the highest EPG. Therefore, we only studied houses that use gas as a heating source. This enabled us to distinguish energy consumed for heating and domestic hot water (and sometimes cooking) on one side, and energy consumed for electrical appliances on the other side.

As this research is primarily focused on testing the effectiveness of the proposed method, for simplicity the sample was reduced to houses with one floor (1469 dwellings), and only houses with an individual gas fired combination boiler for space and domestic hot water heating, reducing the sample further to 876 dwellings. In the Netherlands houses with one floor are mainly apartments. To further reduce the complexity of the calibration we only consider façade insulation, meaning only apartments that are not located under the roof or on the ground floor were taken into account, which reduced the sample to 313 houses. This is significantly less than the initial 4800 cases; however, the sample shows a comparable EPG to the entire sample, and was therefore assumed to be large enough for the method demonstrated in this paper, see fig. 5.2.

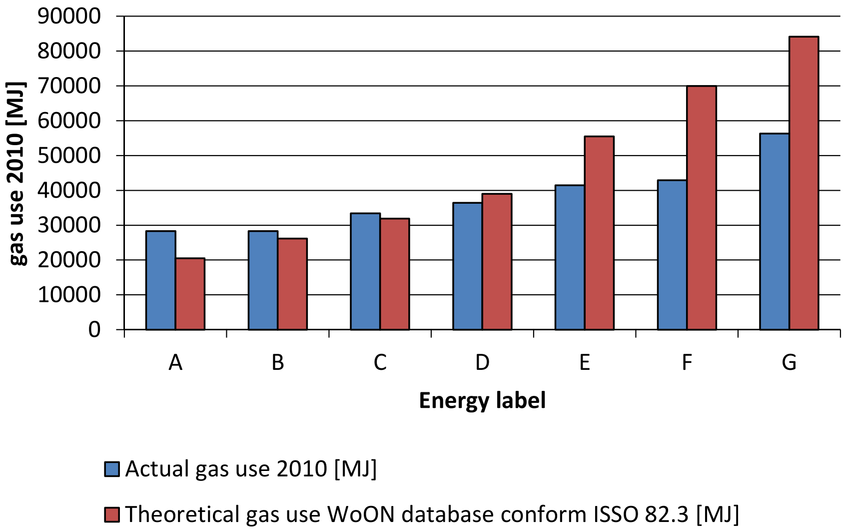

FIG. 5.2 Comparison of actual versus theoretical gas use in buildings based on the WoON database selected sample 313 cases (2012)

5.3.2 Model validation before optimisation

The WoON Energy dataset also contains theoretical energy consumption data. This gave us the opportunity to compare the simulation results of our dynamic building simulation model in Energy Plus with the theoretical energy consumption data in the database. The theoretical energy consumption data in the database is defined by the static Energy labelling method from ISSO 82.3. However, because not all input data was available (such as orientation for each window, height of dwelling, volume of dwelling) some extra assumptions had to be made (see section 5.3.1). Because of this, and because of the slightly different calculation method, it was expected that our simulation results would differ from the results in the WoON database. However, the basic principle should still stand: energy efficient dwellings should use less energy than energy inefficient dwellings in both models. To compare the results, we conducted a linear regression analysis (Figure 5.3 and Figure 5.4).The results show an R^2 of 79% for the steady state and 73% for the dynamic model. This is assumed to be acceptable, which means our dynamic model works and we can continue to the next step. The results also showed that for both models the EPG was present and the magnitude of the gap was comparable. Figure 5.5 and Figure 5.6 also show that the gap is comparable with the gap that we found by using the original WoON data in Figure 5.2.

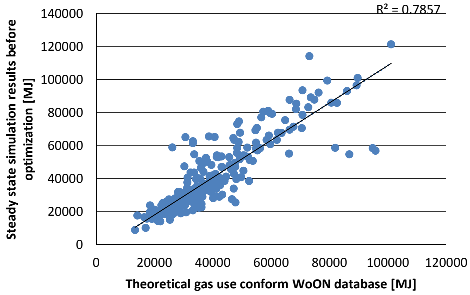

FIG. 5.3 Linear regression Theoretical energy use WoON database versus results steady state simulation model

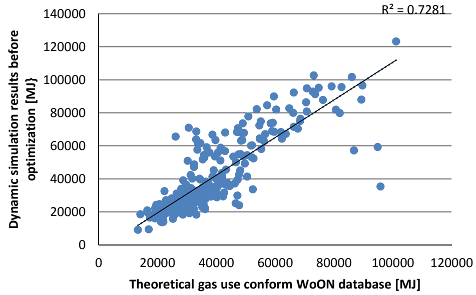

FIG. 5.4 Linear regression Theoretical energy use WoON database versus results dynamic simulation model

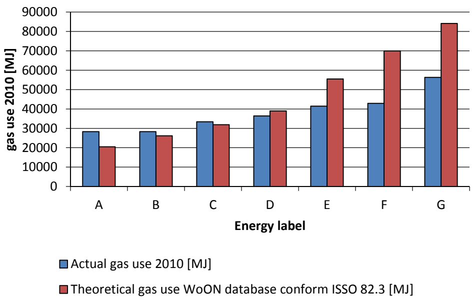

FIG. 5.5 Actual versus Theoretical gas consumption calculated with steady state simulation method

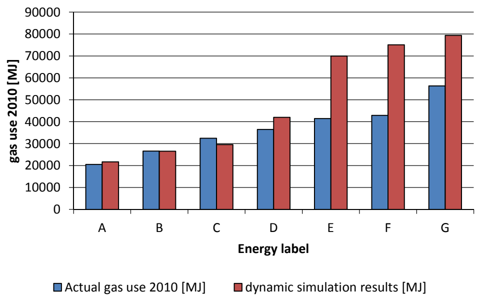

FIG. 5.6 Actual versus Theoretical gas consumption calculated with dynamic simulation method

5.3.3 Sample selection

To demonstrate the method we did not use the entire sample, instead we used a sample representing WoON energy module 2012. We use this representative sample as well as a control group to verify the method.

The selection of the sample has to be completed carefully because each standard value had to occur multiple times to prevent overfitting. Therefore, a complete random selection was not possible. The procedure used for the sample selection was as follows: first a complete random sample of 100 cases was selected. By using frequency tables, we checked whether the optimisation parameters (i.e. the standard values) occurred frequently enough in the sample. If this was not the case, the variable was split per category and for the missing category, a random selection was made. These small random selections were added to the complete random file and all duplicate cases were deleted. For example: in the complete random sample there were almost no houses with a balanced ventilation system. To compensate for this, the file was split in the categories of the ventilation system (natural ventilation, mechanical exhaust ventilation, demand based, and a balanced ventilation system with heat recovery). For the file with a balanced ventilation system with heat recovery, 10 cases were randomly selected and added to the complete random file. This was done for all categories with a number of cases lower than 10. After adding all the extra cases, all the duplicate cases were deleted resulting in a sample of 133 cases. The remaining cases were used as a control group.

5.3.4 Control group selection

Because our sample is relatively small all cases that are not in the sample are used for the control group. If the available dataset is larger, the control group should be randomly selected in the same way as the sample selection. As an ideal, the control group should also be a representative sample of the entire group. Further, depending on the size of the control group, it should be ascertained that there are no influential outliers of actual energy consumption, as these could bias the results.

TABLE 5.2 Frequency of the categories in the dataset

	Frequency total (313 cases)	Frequency sample (133 cases)	Frequency control group (180 cases)
Rc façade			
Measured during inspection	34%	31.7%	35.8%
Assumed in dwellings constructed before 1965	25.9%	26.3%	25.6%
Assumed in dwellings constructed between 1965-1975	4.5%	7.5%	2.3%
Assumed in dwellings constructed between 1975-1988	10.8%	7.5%	13.2%
Assumed in dwellings constructed between 1988-1992	5.8%	7.5%	4.5%
Assumed in dwellings constructed after 1992	19.2%	19.5%	18.9%
Ventilation system			
Natural ventilation	31.0%	30.8%	33.4%
Mechanical exhaust ventilation	53.0%	52.6%	57.1%
Mechanical exhaust ventilation (demand based)	7.7%	8.3%	7.8%
Balanced ventilation with heat recovery	8.3%	8.3%	8.9%
Efficiency space heating system			
Conventional boiler (η<0.80)	0.3%	0%	0.6%
Improved non-condensing boiler (η= 0.8-0.9)	23%	20.3%	26.8%
Condensing boiler (η =0.90-0.95)	3.8%	3.8%	4.1%
Condensing boiler (η >0.95)	72.8%	75.9%	75.5%
Efficiency dhw system			
Hot water boiler (η=0.7)	0.3%	0%	0.6%
Hot water boiler (η=0.8)	23%	20.3%	26.8%
Hot water boiler (η=0.9)	75.8%	79.7%	78.1%
dhw consumption			
dhw floor area <50m2	4.8%	7.5%	3.0%
dhw 50< floor area <75 m2	41.3%	40.6%	44.8%
dhw 75< floor area <100 m2	37.8%	36.1%	41.8%
dhw 100 < floor area <150 m2	15.4%	15.8%	16.2%

5.4 Method

This section describes the proposed method for reducing the average EPG. With the average EPG we mean the average of the difference between theoretical and actual energy consumption of a group of individual dwellings. The first part of this section provides a general description of the method; then the entire procedure is described in detail, and finally some practical information about the implementation of the optimisation problem is given for the steady state and dynamic BES method separately.

5.4.1 General description of the method

The proposed method is inspired by traditional automated calibration methods; however, instead of matching high frequency (hour and less) simulated energy consumption pattern with a high frequency actual energy consumption pattern at an individual building level, the aim is to match simulated annual energy consumption of a housing stock (defined as being a group of houses, typically an apartment building, a neighbourhood, or the asset of an housing association or even the national stock) with actual annual energy consumption data.

An overview of the procedure is given in Figure 5.7. The parameters that we use for the calibration are the standard values of the ISSO 82.3, see Table 5.1 and Table 5.2, i.e.: indoor temperature, Rc value of facades, air change rate and amount of domestic hot water consumption. Because previous studies were based on calibration of indoor temperature only, the indoor temperature is optimized first [20] in order to study how the calibration improves when other variables are added afterwards. In the discussion we come back to the disadvantage of this procedure. This is to avoid some values ‘compensating’ for others. For example, if the real indoor temperature is lower than assumed, the average energy consumption will be lower. The optimisation method could find a lower indoor temperature, but it could also be that it finds higher insulation values for all categories to compensate for the assumption of a high indoor temperature. This interchangeability is one of the risks of optimisation. The optimisation of the indoor temperature is reflected in the upperpart of Figure 5.7 and will be executed as follows: The indoor temperature will be adapted and the individual dwellings will be simulated, then the simulation results are compared with actual energy consumption.

After the indoor temperature is optimised, the other parameters (Rc values façade, ventilation rate and amount of domestic hot water consumption) are optimised following the same procedure as described for the indoor temperature optimisation, however, those are optimised simultaneously.

After the optimisation procedure the results are analysed and finally be tested on the control group.

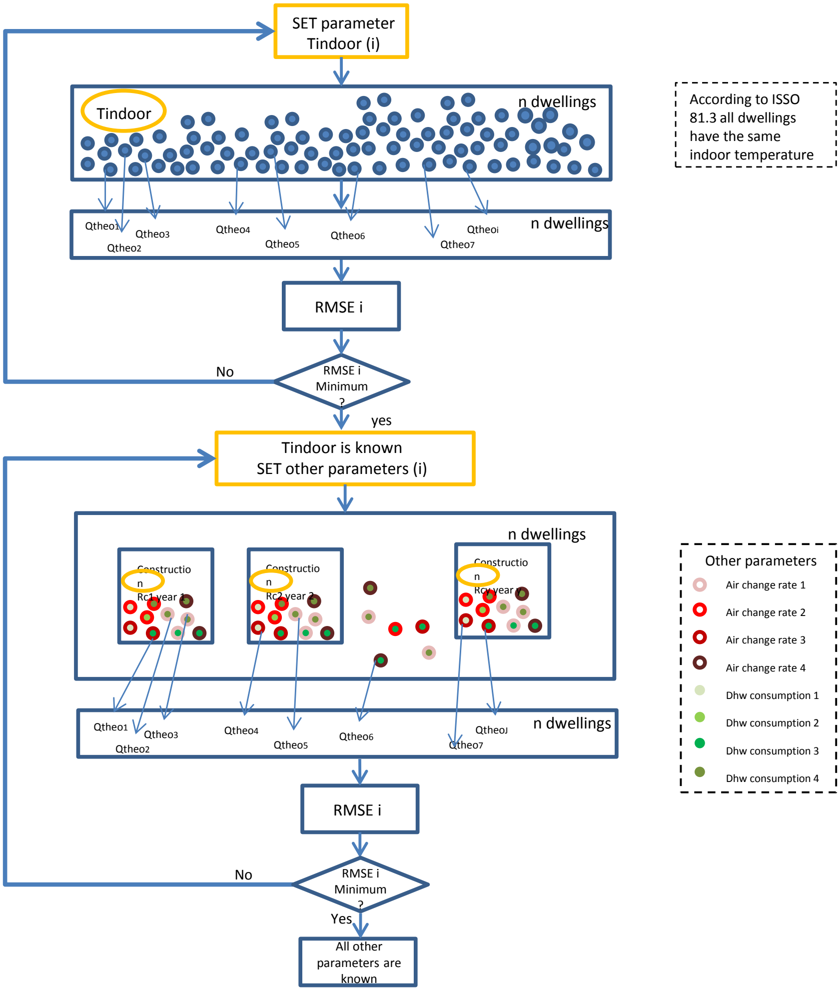

FIG. 5.7 method

5.4.2 Detailed description method

The following paragraphs provide a more detailed overview of the automated calibration method and which aspects are taken into account.

Optimisation problem

For automatic calibration, the Root Mean Square Error is minimized by adapting the assumptions that are made in building simulation models. The Root Mean Square Error is in this case the root of the squared difference between theoretical and actual energy consumption of individual dwellings divided by the total number of dwellings in the sample (eq5.1). The RMSE was chosen instead of the real average difference of theoretical and actual energy consumption to prevent Mean Bias Error. Some dwellings will consume more than expected and others less than expected which could mean that positive and negative differences will cancel each other out. We use the squared difference, as we do in the RMSE, to correct for this problem. This leads to the following objective function:

$$\textbf{Minimise}: \; RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Q_{theo_i} - Q_{act_i})^2}{n}} \qquad \text{EQUATION 5.12}$$

$Q_{theo,i}$ = annual theoretical energy consumption of building *i* [kWh]
$Q_{act,i}$ = annual actual energy consumption of building *i* [kWh]
RMSE = root mean square error
n = number of cases
i = dwelling number

Boundary conditions

As explained, the proposed method focuses on adapting the standard values of the simulation model. This section describes the standard values and their boundary conditions for the Dutch energy label method. As described in Section 5.3, there are many assumptions in the calculation method of the Dutch energy label. All buildings in the database are inspected visually, therefore only 'real' standard values are taken into account (for example, if the Rc-value of the wall is determined by measurement, we consider this value to be accurate, and this value will not be varied (this is also reflected in Figure 5.7 by the circles that are not framed in one of the squares); further, the U-value of the windows are not considered in the optimization either, because it is relatively simple to identify the type of window based on visual inspection. Because our sample does not have sufficient variation in the type of combi gas boilers, the efficiency of the heating and domestic hot water system are not calibrated, however, if a larger and more diverse dataset would be available those could also be calibrated. The following parameters are optimised: Rc value of the façade (for each building period), indoor temperature setting, ventilation in combination with infiltration rate per ventilation system, and domestic hot water consumption. Boundary conditions are defined to reduce the number of possibilities of the optimisation, to make sure that the results will be realistic, and to reduce computation time. The boundary conditions defined for each parameter inTable 5.3. The smaller the range of the assumptions the smaller the search area of the optimisation, and therefore the more likely it will be that the global minimum will be found within an acceptable amount of computation time. A first study has shown that the results can compensate for each other (e.g. a high insulation level can lead to a high ventilation rate and the other way around), therefore it is important that the boundary conditions are chosen properly. However, more research is needed to determine the exact role of the boundary conditions (see also discussion).

The assumptions for the Rc values are based on the requirements of the Dutch building code at the time of construction. For the lower bound the assumed Rc value of the previous category is selected, and for the upper bound the value of the next category is chosen. Because the values of the first two categories (before 1965 and between 1965–1975) are close together they have the same lower bound. In addition, the values of the last two categories (between 1988–1992 and after 1992) are relatively close to each other; therefore, for those cases higher upper bounds are selected. The air change rate in the building is dependent on a combination of infiltration and the type of ventilation system. For the air change rate, an upper bound of 300% and a lower bound of -90% of the initial assumption are selected. For the amount of domestic hot water use (as a lower bound) the average amount of water for one person is selected and as an upper bound the average amount of water for five persons is selected. Relative values for the air change rate and domestic hot water consumption were chosen because those values are dependent on multiple factors and therefore different per individual dwelling (as shown in Table 5.1). The 0% in Table 5.3 can be read as the standard value according ISSO 82.3.

TABLE 5.3 Lower and upper bound of optimization parameters

	Lower bound	Assumed value according ISSO 82.3	Upper bound
Rc value façade [units]			
Before 1965	0.19	0.19	1.3
Between 1965-1975	0.19	0.43	1.3
Between 1975-1988	0.43	1.3	2
Between 1988-1992	1.3	2	3
After 1992	1.3	2.3	3.5
Air change rate			
Natural ventilation	-90%	0%	+300%
Mechanical exhaust ventilation	-90%	0%	+300%
Mechanical exhaust ventilation demand based	-90%	0%	+300%
Balanced ventilation system with heat recovery	-90%	0%	+300%
Indoor temperature setting	15°C	18°C	28°C
Domestic hot water consumption			
dhw floor area <50m2	-39%	0%	286%
dhw 50< floor area <75 m2	-55%	0%	182%
dhw 75< floor area <100 m2	-65%	0%	142%
dhw 100 < floor area <150 m2	-67%	0%	133%

** 0% means that the standard values of ISSO 82.3 is used*

Optimisation algorithm

Now the optimisation problem and the boundary conditions are known, an optimisation algorithm is required. Due to the high computation time and relatively high number of variables, a ‘brute-force’ optimisation (calculating every possible scenario) is not possible. Therefore, the Global Optimisation Toolbox in Matlab is used. This toolbox has several predefined optimisation algorithms that can be used for optimising a function. Because our objective function is the RMSE which results from the energy simulation of all buildings in the sample, the computation time per run is relatively high (especially when the dynamic simulation model is used), making the optimisation process relatively slow. Therefore, it is important to choose an efficient optimisation algorithm. The function that we will optimise is a nonlinear function which has multiple local minima, and therefore only global optimisation methods are suitable for this optimisation. Some of the possible predefined optimisation algorithms (available in Matlab) are pattern search, genetic algorithm, simulated annealing, particle swarm optimisation, surrogate optimisation, and the global search method. Due to the relatively high computational requirements for the dynamic simulations, the surrogate optimisation model is assumed to be the best method to use for optimizing the parameter settings of the assumption in the dynamic building simulation method. However, other optimisation algorithms can be applied on the steady state model because this model requires significantly less computation time. Therefore, the particle swarm optimisation method is used for the steady state optimisation. The particle swarm method is selected because a comparison of different optimisation algorithms by Matlab showed that it requires relatively few iterations, which means the method is relatively fast [27, 28].

Analysing the optimised parameters

To test if the optimized settings used in the assumptions indeed reduce the energy performance gap the RMSE of the simulations with the initial assumptions and the RMSE of the simulation with the optimised parameters are compared. If the RMSE reduces, this is an indication that the gap reduces. A second test that is done is a linear regression of actual energy consumption versus theoretical energy consumption with the initial and the optimised parameters. If the R^2 of the regression with the optimised parameters is higher it means that the simulation model indeed predicts better with the optimised parameters. Finally a similar graph as shown in Figure 5.1 is made to show the reduction of the average energy performance gap.

Influence of optimised parameters on RMSE

After the automated calibration the optimised parameters are studied more in depth to check if the optimisation indeed performed as expected. We would expect that each optimised parameter has an effect on the reduction of the RMSE. To test this 15 more simulations were executed.

The first simulation showed the results with all optimised parameters. The second simulation showed the results with all optimised parameters, except for indoor temperature, the third with optimised parameters except for the Rc values of façades from before 1965, and so on. By comparing the RMSE of the simulations, it is possible to determine whether the individual parameters contribute to a lower RMSE and is therefore a better assumption that the initial one. If the optimisation functions as desired all simulation results will lead to a higher RMSE than the simulation in which we used all optimised parameters.

Because not every category of assumption occurs the same amount of times in the database the above method does not provide information about the amount of influence of each parameter category on the RMSE. Therefore, to determine which standard values have the highest impact, another four extra simulations were executed, whereby we use the optimised parameters except for one parameter category. For example, to determine the importance of the insulation rate of the façade we compared the RMSE of the optimised results with the RMSE of the simulation results of the sample with the initial standard values for the insulation rate, and optimised standard values for all other parameters. A larger difference indicates that the optimised results have a higher impact on the RMSE.

5.4.3 Practical implementation of co-simulation

Because Matlab was used for the optimisation and because the steady state simulation is relatively simple, the simulation model was rebuilt in Matlab according to the description in 2.1.1 and could be directly connected to the optimisation algorithms in Matlab. In addition to the steady state simulation, we also tested the method using a dynamic simulation method. In general, the method works exactly the same as for the steady state method. However, for the dynamic simulation we decided to use the external software EnergyPlus, which meant that a connection of this software and the optimisation tool in Matlab was required. Energy Plus was chosen because this is validated software that is widely recognised in the field.
To connect EnergyPlus with Matlab, the co-simulation toolbox was used, which facilitates the communication between EnergyPlus and Matlab. The toolbox used the Building Control Virtual Test Bed (BCVTB), which is a software environment that allowed us to couple different simulation programs to each other for co-simulation [29]. Figure 5.8 shows an overview how this connection between Matlab and EnergyPlus was made.

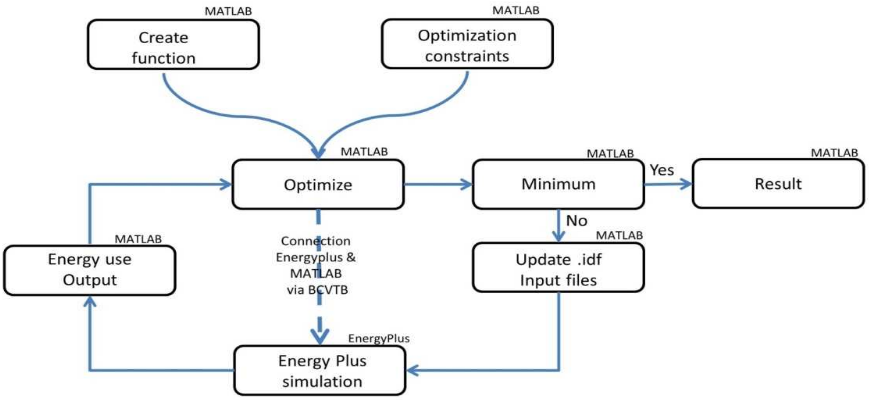

FIG. 5.8 Overview of connection Matlab and EnergyPlus

As Figure 5.8 shows, to connect Matlab and EnergyPlus, several input files had to be prepared. First, we defined which parameters were to be optimised, and which would remain fixed for every building. Then, for every building in the sample, an .idf file was created in Matlab, (automated by using the find and replace function). This produced an .idf file available for every building, containing the geometry and window characteristics data. In our study, by using the replacing string function, all parameters that differed per dwelling (but were not supposed to be optimised) were replaced by their number from the WoON database, for example floor area, volume, façade area, U-value of the window, and measured insulation values. This resulted in 133 separate .idf files for the sample and 180 files for the control group.

5.5 Results

This section presents and analyses the results of the optimisation for both the steady state and the dynamic BES model. The results will be presented in the same order as described in the method section. The first part presents the optimisation results of the dynamic and steady state models. After this the results are analysed. In the third section we study the influence of the optimised standard values on the RMSE, and

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finally we show the effectiveness of the method by applying the optimised standard values on a control group. Because we applied the method on both a steady state and dynamic simulation model, the results are shown for both examples.

5.5.1 Optimisation results

As described in the method section and presented in Figure 5.7 first, the indoor temperature is optimised and afterwards the other variables are optimised simultaneously.

Optimisation indoor temperature

For the optimisation of the indoor temperature in the steady state method we applied two optimisation algorithms, the surrogate and the particle swarm optimisation method. The reason why we tried both is to check if both would result in the same result and this was indeed the case. For the steady state method we found an average indoor temperature of 16.2 °C. A comparison of the optimisation methods indicates that the number of required simulations to come to this value is lower for the surrogate method; however, the computation time is almost the same. A reason for this is that the surrogate model requires more computational power to determine the next best guess than the particle swarm method. Therefore, the particle swarm method is indeed better for the steady state simulation, because it can achieve more simulations in the same amount of time than the surrogate model; therefore, the probability of finding the global minimum will be higher. However, for the dynamic BES model, the simulation time is decisive, making the surrogate model a preferable method.

The calibrated indoor temperature of 16.2 °C of the steady state simulation is significantly lower than the assumed constant average indoor temperature of 18 °C in the actual method. This may be because on average people use lower heating temperature, or heat the house less at night, or do not heat the complete floor heated area. For the dynamic model, using the surrogate model, we found an even lower indoor temperature of 15.9 °C. Optimisation of the indoor temperature reduces the RMSE 6% for the steady state model and 15% for the dynamic building simulation model. A linear regression between actual energy use and theoretical energy consumption after optimization did not result in a significant improvements of the R^2.

Optimisation façade insulation, air change rate and DHW consumption

After the indoor temperature is calibrated it is used as fixed input and the other parameters are optimised simultaneously. Due to time restrictions, the dynamic simulation model ran fewer simulations than the steady state simulation model. In total, the optimisation of the dynamic simulation model ran 1100 iterations, from which each iteration contained one run of simulation of the entire sample. For the steady state model the particle swarm method was applied, slightly more than 90 iterations were executed, from which each iteration contained 100 simulations of the entire sample (Figure 9-13). The computation time for the dynamic model was six days on a computer with a CPU of 3.2 GHz, using one core. The optimisation of the steady state model took a little bit under 10 minutes. However, both show a significant improvement in the RMSE (25% for the steady state model and 27% for the dynamic model). A linear regression of the theoretical energy consumption versus actual energy consumption shows an increase of 10% of the R^2 (18% before optimisation and 28% after optimisation) for the steady state model (see Figure 5.9 and 5.11). The dynamic model shows an increase of 5% (15% before optimisation and 20% after optimisation) (see Figure 5.10 and 5.12). All these factors indicate that the model predicts the heating energy more effectively with the optimised parameters/standard values (see sections 5.5.2 for these values).

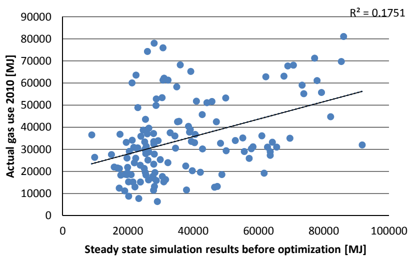

FIG. 5.9 Regression actual energy use versus steady state simulated energy use before optimisation on sample

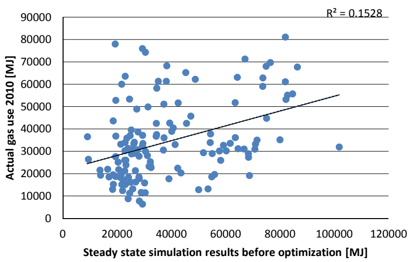

FIG. 5.10 Regression actual energy use versus dynamic simulated energy use before optimisation on sample

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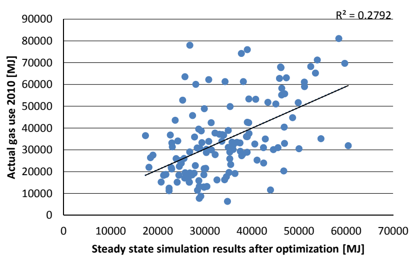

FIG. 5.11 Regression actual energy use versus steady state simulated energy use after optimisation on sample

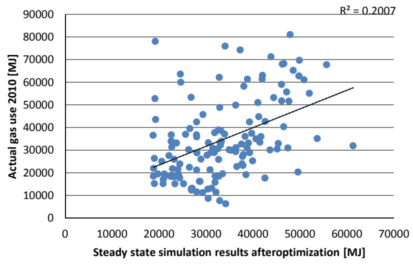

FIG. 5.12 Regression actual energy use versus dynamic simulated energy use after optimisation on sample

For the resulting average EPG in each label category, the use of the optimised standard values leads to a significant improvement. A comparison is presented in Figure 5.13 and 5.15 for the steady state simulation and Figure 5.14 and 5.16 for the dynamic simulation, showing that in each label category the average consumption is much closer to the actual one and therefore the average EPG reduced significantly when optimised standard values were applied in the simulation method.

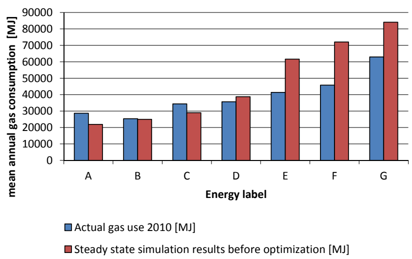

FIG. 5.13 Actual versus theoretical gas consumption calculated with steady state simulation method before optimisation - sample

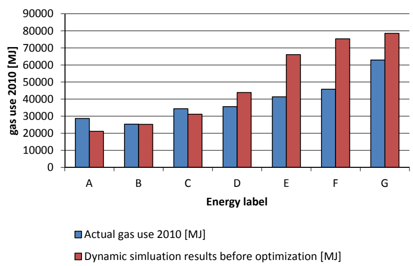

FIG. 5.14 Actual versus theoretical gas consumption calculated with dynamic simulation method before optimisation - sample

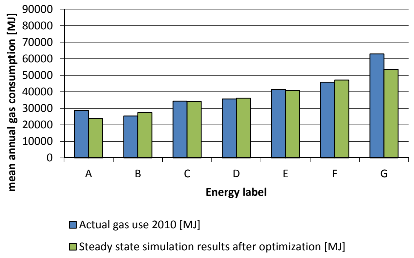

FIG. 5.15 Actual versus theoretical gas consumption calculated with steady state simulation method after optimisation - sample

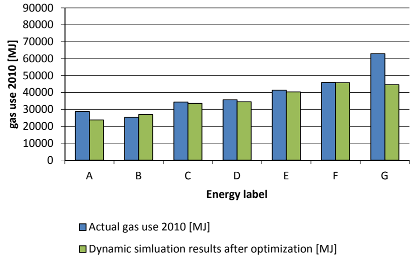

FIG. 5.16 Actual versus theoretical gas consumption calculated with dynamic simulation method after optimisation - sample

5.5.2 Control group results

For the optimisation, we used a sample of the entire dataset. The follow-up analyses show that the optimisation works for the sample. However, the main aim of the method was that the optimized standard values could be used for better prediction of the entire building stock. Therefore, the buildings in the control group were simulated twice with a dynamic and steady state simulation method. The first simulation used the standard values recommended in ISSO 82.3 and the second simulation used the optimised standard values. If the method works, the average EPG should also be reduced for the control group. The results are shown in Figure 5.17–5.25 and they indeed show that the gap was significantly reduced; this indicates that the method functioned as expected and is therefore an effective method for reducing the average EPG to make building simulation models a more useful tool for policymakers.

The RMSE of the control group reduced significantly with the adapted standard values. The RMSE reduced from 23002.82 MJ to 16454.25 MJ, a reduction of 28% for the steady state method and from 18842.40 MJ to 25884.64 MJ, a reduction of 27% for the dynamic simulation method (see figure 5.17-5.20). Moreover, the R^2 of the linear regression between actual energy consumption and theoretical energy consumption showed a significant improvement. Before optimisation, we found for the steady state method an R^2 of 12.4% and after the optimisation the R^2 increased to 21.3%, in the dynamic method we found an improvement of the R^2 of 4% (see figure 5.21-5.24). The main aim of the optimisation was to reduce the average performance gap by optimising the standard values in the BES models

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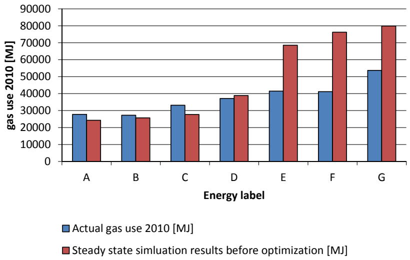

FIG. 5.17 Actual versus theoretical gas consumption calculated with steady state simulation method before optimisation – control group

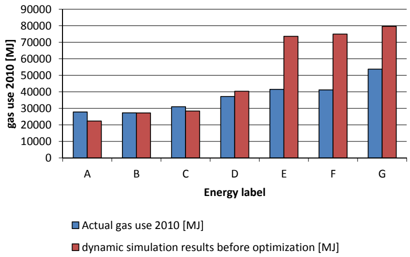

FIG. 5.18 Actual versus theoretical gas consumption calculated with dynamic simulation method before optimisation – control group

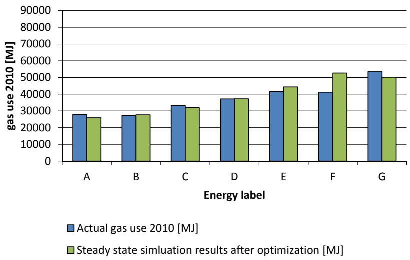

FIG. 5.19 Actual versus theoretical gas consumption calculated with steady state simulation method after optimisation – control group

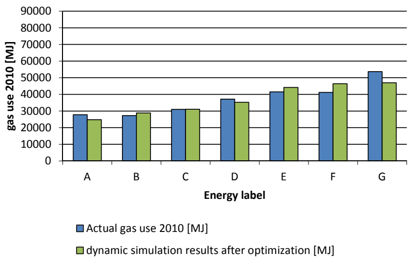

FIG. 5.20 Actual versus theoretical gas consumption calculated with dynamic simulation method after optimisation – control group

Therefore, although we are not certain the optimised parameters are fully representative of the reality and further research is needed (see sections 5.6, 5.7), this method shows that it is possible to generate data-driven standard values for the model that seem realistic and lead to a more accurate prediction of the average energy consumption in a specific building stock.

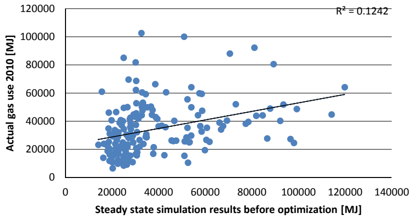

FIG. 5.21 Regression actual energy use versus steady state simulated energy use before optimisation on control group

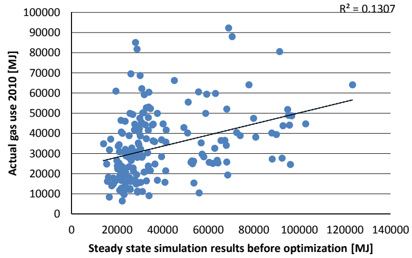

FIG. 5.22 Regression actual energy use versus dynamic simulated energy use before optimisation on control group

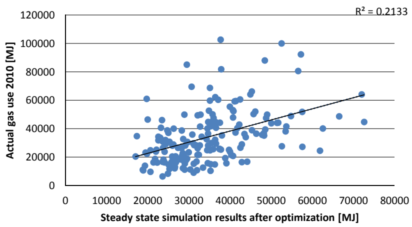

FIG. 5.23 Regression actual energy use versus steady state simulated energy use after optimisation on control group

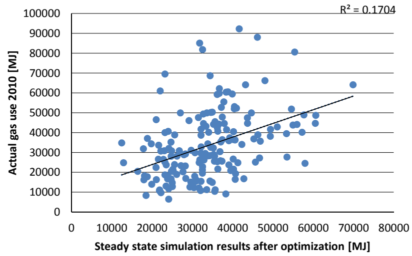

FIG. 5.24 Regression actual energy use versus dynamic simulated energy use after optimisation on control group

5.5.3 Analysis of the optimised standard values

The optimised standard values are presented in Table 5.4. The results for the dynamic and steady state models are slightly different. This is logical because the calculation method is also slightly different.

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The results indicate that in general, the insulation rate of the façade was underestimated for buildings built before 1965 and between 1965 and 1975, which is in accordance with previous research [22]. For dwellings built between 1975 and 1992, an overestimation was detected, whereby the buildings are in reality less insulated than assumed. For the insulation rate of buildings built after 1992, the results show a higher number than initially assumed. A possible explanation for this is that a relatively large number of dwellings in the category “>1992” were constructed after 2000. In 2000, the energy performance coefficient (an indicator for energy-efficient state of new built buildings in the Netherlands) became stricter. To achieve this coefficient, it is possible the buildings were constructed with a higher Rc value than required according to the building decree.

For the indoor temperature, we found a significantly lower indoor temperature than the assumed 18 °C. A possible explanation for this is that our model assumes the entire building is constantly heated up to 18 °C, although in reality heating is often lowered during the night and bedrooms are (in the Netherlands) often not heated at all [30, 31], which makes a lower average indoor temperature a more realistic assumption.

For the air change rate (based on a ventilation system) we found that buildings with natural ventilation have a lower ventilation rate than buildings with mechanical exhaust ventilation, although the ISSO 82.3 method assumes that they have the same amount of compulsory ventilation. The results seem legitimate as mechanical systems are installed to remedy for poor natural air flows. Further, for demand-based ventilation, the optimisation suggested higher ventilation rates. This could be possible because in reality people also open the window next to their ventilation system. For the balanced ventilation system, we found different results for the dynamic and the steady state models. A possible explanation is that the heat loss of dwellings with a balanced ventilation system and heat recovery was so low that the amount of ventilation had a limited impact, which provided inconclusive results. On average the optimised standard values suggest a higher ventilation rate should be assumed.

According the standard values in ISSO 82.3, the amount of hot water used is highly dependent on the floor area category the dwelling belongs, however, the optimisation results show that the amount of domestic hot water used does not differ that much for the two smallest floor area categories. The results of this optimisation could indicate that the categorisation of domestic hot water consumption might not be accurate. This could be because actual DHW is expected to depend directly from the number of persons living in the house, rather than from the m^2 and the (in the norm) expected relationship between number of people and floor area is rather weak.

TABLE 5.4 Optimised parameters for the steady state and dynamic simulation methods

	Initial assumption (ISSO 82.3)	optimised parameters of steady state BES model	optimised parameters of dynamic BES model
Façade insulation			
<Rc1965	0.19	0.49	0.41
Rc1965-1975	0.43	0.51	0.78
Rc 1975-1988	1.3	0.75	1.1
Rc 1988-1992	2	0.88	1.45
>Rc 1992	2.3	3.1	3.1
Ventilation and infiltration rate			
Natural ventilation	0%	+31%	+42%
Mechanical exhaust ventilation	0%	+88%	+75%
Mech. Exh. Demand based	0%	+124%	+20%
Balanced with heat recovery	0%	+30%	-17%
Indoor temperature	18 °C	16.2 °C	15.9 °C
Domestic hot water consumption			
dhw floor area <50m2	0%	+135%	+166%
dhw 50< floor area <75 m2	0%	-5%	+17%
dhw 75< floor area <100 m2	0%	+21%	+42%
dhw 100 < floor area <150 m2	0%	-3%	+30%

** 0% is initial value according ISSO 82.3*

5.5.4 Influence of optimised parameters on RMSE

To test if all parameters were optimised, another 15 simulations were made for both methods. In each run, we used the optimised values except for one variable; for that variable we use the original input as described in ISSO 82.3. If the RMSE was higher than the optimisation result we could conclude that the changed assumption indeed reduced the performance gap. If the RMSE was higher than the optimised RMSE, we could conclude that for that particular variable the initial value would have been better. The results are shown in Table 5.5 and indeed indicate that each parameter resulted in a lower RMSE.

TABLE 5.5 Change RMSE for different variables analysis

	RMSE steady state simulation [MJ]	RMSE dynamic simulation [MJ]
Optimised	14758.68	15622.52
Façade insulation		
<Rc1965	15420.6	17762.94
Rc1965-1975	14886.93	15622.52
Rc 1975-1988	14783.96	15626.04
Rc 1988-1992	14764.02	15683.77
>Rc 1992	15071.67	15634.48
Ventilation and infiltration rate		
Natural ventilation	14829.24	15760.99
Mechanical exhaust	16092.82	16541.27
Mechanical exhaust demand based	14904.58	15633.16
Balanced ventilation with heat recovery	14794.00	15628.52
Indoor temperature	16250.83	17939.97
Domestic hot water consumption		
DHW floor area <50 m2	14868.23	15923.66
DHW floor area ≥50 m2 & <75m2	14760.15	15739.68
DHW floor area ≥75 m2 & <100m2	14814.43	15944.59
DHW floor area ≥100 m2 & <150m2*	14759.16	15741.72

** there are no dwellings with a floor area > 150m2 in the dataset*

To determine which optimized parameter had the highest impact on the performance gap, four extra simulation runs were completed (see Table 5.5). In these runs, we again used the optimised values except for one of the four optimised parameter categories (façade insulation, air change rate, indoor temperature, and domestic hot water consumption). The results of the steady state model showed that the adapted parameter settings for the insulation rate had the highest impact followed by the ventilation rate, indoor temperature, and finally the amount of domestic hot water consumption. This is in accordance with previous studies on the sensitivity of parameters in building energy simulation models [32]. The results of the dynamic simulation method were similar, with the exception of indoor air temperature. The indoor air temperature for the dynamic simulation model was the parameter with the greatest influence. In the previous results, we already saw that the optimized parameter setting for indoor air temperature for the dynamic simulation model was lower than the optimized parameter setting for temperature for the steady state model. It is understandable that this is also reflected in the RMSE. It shows the sensitivity of building simulation models climate data.

TABLE 5.6 determining the influence of the optimisation per parameter

	RMSE steady state [MJ]	RMSE dynamic simulation [MJ]
Optimised results	14758.68	15622.52
Façade insulation	17288.78	17772.04
Air change rate	16322.93	16687.69
Indoor temperature	16250.83	17939.97
Domestic hot water consumption	14925.49	16466.4

5.6 Discussion

This research introduced the first step towards a method to reduce the average performance gap on a building stock level. The results show that calibrated standard values use in BES by using optimization algorithms is a powerful way of reducing the average performance gap. However, the optimised parameters from this research should not directly be used as new assumptions for the Dutch energy label calculation method. One of the reasons is that in our analysis we only used apartment buildings with a gas heating system, which means the dataset is not representative of the entire housing stock. Because our sample only included a limited number of different efficiencies of the heating and domestic hot water systems, we decided not to optimise the efficiency of those systems. Because we did optimise the indoor temperature separately, it could be that the optimised indoor temperature corrects for the efficiency of the heating system. It is therefore recommended to search for a more secure procedure in the future where all variables would be optimized concurrently.

During the study, it was found that the boundary conditions used for the optimisation have a significant influence on the outcome, especially the computation time. In this study, the boundary conditions were based on a theoretical background and previous research results; however, more sample measurements should be completed to determine whether the chosen boundary conditions are the most appropriate.

A drawback of this method is that actual energy consumption data of multiple houses with different characteristics needs to be available. This is not the case in every country; however, in many countries there is a recurring survey that monitors the national building stock. These data could be used to optimise the parameter settings

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used in the assumptions (for example, in the Netherlands, the WoON database; in Denmark Statistics Denmark administrative registers and Danish Building and Dwelling Register (BBR); and in the UK the “English Housing” survey).

Although the results seem promising, we should keep in mind that we used an optimisation algorithm and not the brute force method, which makes it possible that there might be better assumptions possible than the ones we found. This brings us directly to the following point of the physical meaning of optimised parameters. Similar to traditional calibration techniques and other reversed engineering methods, this method does not ensure that adaptions made in the assumptions are a realistic reflection of reality. This is also demonstrated by the differences in results for the dynamic and steady state simulation models.

5.7 Conclusions and policy implications

This research introduced the first steps towards a method to reduce the average EPG, by adapting standard values in building energy simulation model to make building simulation models a more reliable tool for policymakers. The research showed that the EPG of both the steady state and dynamic models are comparable. The case studies prove that the RMSE can be reduced by approximately 25%–27% and the R^2 can be improved by 4–10%. For both steady state and dynamic simulation models, the method reduced the average EPG significantly. The results seem promising, although in the discussion section we already mentioned some potential room of improvement More research is needed to make the method more reliable and practically usable. The following aspects should be investigated in further research:

- What are the exact conditions that the optimisation sample and control groups should fulfil to increase the reliability of the optimisation results (e.g. how many cases are needed per parameter)?
- Having strict boundary conditions will speed up the optimisation process and therefore increase the probability of finding the correct results. More research should be done towards the lower and upper boundary conditions of each parameter and to which extent they are active or inactive.

- More research should be completed for the best metric for the optimisation model. In this case we used the RMSE; however, it is possible that this increased the overfitting probability because outliers have a heavier weight than when (for example) the mean absolute error would have been used.

- Although a significant reduction of the EPG was achieved in this research, it is possible that a higher reduction could be achieved. For example, the indoor temperature is now the same for every dwelling but previous research has shown that the indoor temperature is dependent on the energy efficiency of the houses (high energy efficient dwellings have a higher average indoor temperature compared to low energy efficient dwellings). Optimisation of indoor temperature for different categories might reduce the EPG even further [33], but this would lead to a 'new' method.

- More attention should be paid from a mathematical point of view to what parameters under which conditions can really be optimised without the risk of interchangeability and which nonlinear constraints are necessary. These non-linear constraints may also make it possible to optimise all parameters simultaneously instead of optimising the indoor temperature first. .

Despite the extra research that is needed, the first results of the method seem promising and with some additional research we believe that the average EPG can be significantly reduced, which would make building simulation tools a more reliable tool for policymakers. Average energy consumption and energy savings on a building stock level will be predicted more accurately which will enable more realistic energy saving targets. The method would be especially useful for example for the EPBD. Every country has its own simulation model, with their own assumptions. However, by using the proposed calibration method, the simulation models can be calibrated at the same level and improved. Countries can keep their own simulation models but the calibration of the model can be made transparent and improved by adapting the assumptions. This makes the models comparable and makes it possible to compare the outcomes of the simulation models with each other. This is especially important because the EPBD is currently not only used as a source of information for potential buyers and/or tenants, but is also used as a monitoring tool by both, European and national policymakers.

Some important aspects that should be taken into account when using the proposed method, which is summarized in Figure 5.25 are

2 Having enough cases per optimization parameter
3 Make sure that the group is representative
4 Prevent overfitting
5 Avoid influential outliers because they will have a significant influence on the end result
6 This method does not aim to reduce the gap between predicted and actual energy consumption on an individual building level but only on a building stock level

This research did not only present a new effective method to make better assumptions for more realistic BES results, but it also showed how much influence the assumptions have on BES results This should be taken into account by policymakers when preparing new calculation norms for building energy consumption. This research once again shows the importance of monitoring real energy consumption data and shows that it is still important to gather this type of data in order to be able to learn from this data.

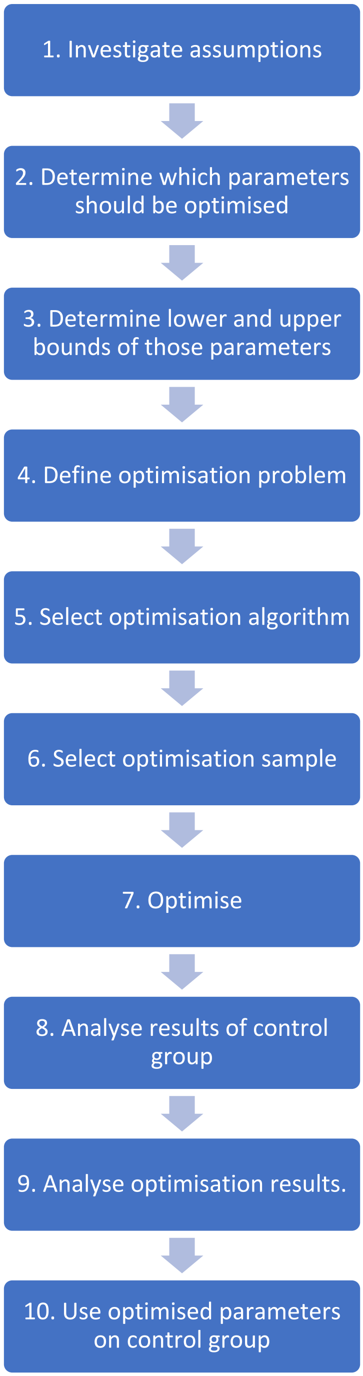

FIG. 5.25 Summary of proposed method

References

[1] Eurostat, *Final energy consumption by sector*, t2020_34, Editor. 2016: https://ec.europa.eu/eurostat/web/products-datasets/-/T2020_34.

[2] Crawley, D.B., *Building Performance Simulation: A Tool for Policymaking*, in *Department of Mechanical Engineering*. 2008, University of Strathclyde: Glasgow, Scotland, UK. p. 307.

[3] Hamilton, I.G., et al., Energy efficiency in the British housing stock: Energy demand and the Homes Energy Efficiency Database. Energy Policy, 2013. 60: p. 462-480

[4] de Wilde, P., *The gap between predicted and measured energy performance of buildings: A framework for investigation.* Automation in Construction, 2014. **41**: p. 40-49.

[5] Majcen, D., L. Itard and H. Visscher, *Actual and theoretical gas consumption in Dutch dwellings: What causes the differences?* Energy Policy, 2013. **61**: p. 460-471.

[6] Guerra Santin, O., *Occupant behaviour in energy efficient dwellings: evidence of a rebound effect.* Journal of Housing and the Built Environment, 2013. **28**(2): p. 311-327.

[7] Menezes, A.C., et al., *Predicted vs. actual energy performance of non-domestic buildings: Using post-occupancy evaluation data to reduce the performance gap.* Applied Energy, 2012. **97**: p. 355-364.

[8] Sunikka-Blank, M. and R. Galvin, *Introducing the prebound effect: the gap between performance and actual energy consumption.* Building Research & Information, 2012. **40**(3): p. 260-273.

[9] Cozza, S., J. Chambers and M.K. Patel, Measuring the thermal energy performance gap of labelled residential buildings in Switzerland. Energy Policy, 2019: p. 111085

[10] Galvin, R., *Making the 'rebound effect' more useful for performance evaluation of thermal retrofits of existing homes: Defining the 'energy savings deficit' and the 'energy performance gap'.* Energy and Buildings, 2014. **69**: p. 515-524.

[11] Filippidou, F., N. Nieboer and H. Visscher, *Effectiveness of energy renovations: a reassessment based on actual consumption savings.* Energy Efficiency, 2018.

[12] Majcen, D., L. Itard and H. Visscher, *Energy labels in Dutch dwellings - their actual energy consumption and implications for reduction targets*, in *ECEEE 2013 Summber study - rethink, renew restart*. 2013.

[13] van den Brom, P., A. Meijer and H. Visscher, *Performance gaps in energy consumption: household groups and building characteristics.* Building Research & Information, 2017: p. 1-17.

[14] van den Brom, P., A. Meijer and H. Visscher, *Actual energy saving effects of thermal renovations in dwellings—longitudinal data analysis including building and occupant characteristics.* Energy and Buildings, 2019. **182**: p. 251-263.

[15] van den Brom, P., et al., *Variances in residential heating consumption – Importance of building characteristics and occupants analysed by movers and stayers.* Applied Energy, 2019. **250**: p. 713-728.

[16] Majcen, D., L.C.M. Itard and H. Visscher, *Theoretical vs. actual energy consumption of labelled dwellings in the Netherlands: Discrepancies and policy implications.* Energy Policy, 2013. **54**: p. 125-136.

[17] EU, *amending Directive 2010/31/EU on the energy performance of buildings and Directive 2012/27/EU on energy efficiency*, in *L 156/75*, E. Parlement, Editor. 2018, Offical Journal of the European Union: Strassbourgh. p. 17.

[18] Filippidou, F., N. Nieboer and H. Visscher, *Are we moving fast enough? The energy renovation rate of the Dutch non-profit housing using the national energy labelling database.* Energy Policy, 2017. **109**(Supplement C): p. 488-498.

[19] Coakley, D., P. Raftery and M. Keane, *A review of methods to match building energy simulation models to measured data*. Renewable and Sustainable Energy Reviews, 2014. **37**: p. 123-141.

[20] Heo, Y., R. Choudhary and G.A. Augenbroe, *Calibration of building energy models for retrofit analysis under uncertainty*. Energy and Buildings, 2012. **47**: p. 550-560.

[21] Gram-Hanssen, K., *Households' energy use - which is the more important: efficient technologies or user practices?*, in *World Renewable Energy Congress 2011*, EEE, Editor. 2011: Linkoping, Sweden.

[22] Rasooli, A., L. Itard and C.I. Ferreira, A response factor-based method for the rapid in-situ determination of wall's thermal resistance in existing buildings. energy and buildings, 2016. 119: p. 51-61.

[23] Rijksoverheid.nl., WoON2012 energie module, BZK, Editor. 2014.

[24] ISSO, *Energieprestatie advies woningen*, in *82.3*, ISSO, Editor. 2011: Rotterdam.

[25] DesignBuilder, *Version 3.0.0.043. 2000-2009*; Available from: www.designbuildersoftware.com.

[26] ECN, energie-nederland and Netbeheer-nederland, *energietrends 2014*, in *energietrends*. 2014.

[27] Matlab. *Particle Swarm Optimisation Algorithm*. 2019; Available from: https://nl.mathworks.com/help/gads/particle-swarm-optimisation-algorithm.html.

[28] Goy, S., *Towards smarter cities: On the potential of Model Predictive Control for energy saving and increased exibility in the built environment*, in *School of Mechanical and Materials Engineering, College of Engineering and Architecture*. 2019, University College Dublin: Dublin. p. 302.

[29] Nouidui, T. *Building Controls Virtual Test Bed*. 2016 2016-04-22 [cited 2019 26-2]; Available from: https://simulationresearch.lbl.gov/bcvtb/FrontPage.

[30] Majcen, D., L. Itard and H. Visscher, *Statistical model of the heating prediction gap in Dutch dwellings: Relative importance of building, household and behavioural characteristics*. Energy and Buildings, 2015. **105**: p. 43-59.

[31] Guerra-Santin, O. and L. Itard, *Occupants' behaviour: determinants and effects on residential heating consumption*. Building Research & Information, 2010. **38**(3): p. 318-338.

[32] Ioannou, A. and L.C.M. Itard, *Energy performance and comfort in residential buildings: Sensitivity for building parameters and occupancy*. Energy and Buildings, 2015. **92**: p. 216-233.

[33] Guerra Santin, O., L. Itard and H. Visscher, *The effect of occupancy and building characteristics on energy use for space and water heating in Dutch residential stock*. Energy and Buildings, 2009. **41**(11): p. 1223-1232.

6 Conclusions and recommendations

6.1 Introduction

This thesis investigated if and to what extent occupant and building characteristics explain the gap between theory and practice of building energy consumption. Further, it introduced a method to reduce this gap on a building stock level by using actual energy consumption data. The study made use of large databases with actual and theoretical annual energy consumption data, occupant characteristics data and building characteristics data on an individual dwelling level. The main reason for this study is that reducing residential energy consumption is high on the political agendas of many countries. Up to now, energy-saving policies, subsidies, and action plans, as well as energy monitoring, are often based on theoretical energy consumption and savings, whereas energy-saving targets are expected to meet actual energy savings [1-4]. Because there is a significant gap between theoretical and actual energy consumption the saving targets are often not met [5]. It is therefore important to get a better insight into this gap and, if possible, reduce it. One of the strengths of this study compared to existing ones is that large databases with actual and theoretical annual energy consumption on an individual dwelling level are used, not only containing building characteristics data but also occupant characteristics data.

Theoretical energy consumption can be calculated by several methods. This study mainly uses the calculation method from the Dutch government that was used until 2014 to determine the energy label (energy performance certificate) of a house. This method is based on a steady state method. The theoretical energy consumption results of the energy label calculation method are widely used in the Netherlands, e.g. to determine subsidies and rent limits and to conduct energy-saving action plans. Some people suggest that the cause of the energy performance gap is the oversimplified steady state method used by the Dutch government, however, chapter

5 of this thesis showed that the energy performance gap is also present in dynamic simulation models .

This study was only possible due to a variety of data sources. The first is the SHAERE database, which contains the building characteristics data of a significant number of social rental houses in the Netherlands. It also contains energy labels (energy performance certificate) and the corresponding theoretical energy consumption. The SHAERE database is updated every year, which makes it possible to follow the changes in building characteristics over the years. The second data source is from Statistics Netherlands. This database contains actual energy consumption provided by the energy supply companies in the Netherlands at address level. Statistics Netherlands also has data available at the person level, which can be linked to the addresses. Because the information from Statistics Netherlands is privacy sensitive, the data can only be used in a protected environment and research results are only allowed to be exported on an aggregated level (at least 10 cases or more). Another dataset that was used is data on building and household characteristics from Statistics Denmark's administrative registers, which cover the full population of Denmark. These were merged with data on household energy consumption for space heating and hot water from the Danish Building and Dwelling Register (BBR), which is part of the Danish Ministry of Taxation. The WoON database, which is the last data source, is based on a survey carried out by the Dutch government to gather information on the energy performance of the Dutch dwelling stock. This research is carried out every 5 to 6 years. In this study, we used the results of the WoON energy survey for 2012, which was the most recently available dataset.

This study is split into four key questions, each represented in one chapter of the thesis. In the second chapter, the relationship between occupant groups and building characteristics with the energy performance gap was explored. Because previous studies showed proof of a relationship between behaviour and the energy performance of a building, the relationship between the energy performance gap and occupant groups was studied with regard to the energy label. Following this, more detailed information was gathered by comparing the characteristics of the highest and lowest 10% energy-consuming groups.

One of the most important consequences of the energy performance gap is that the energy savings of thermal renovations are often lower than expected. Because of this, almost 90,000 renovated houses are studied to determine if there is a relationship between the building and occupant characteristics and the magnitude of the energy savings, as well as the energy saving gap (see chapter 3). First, the actual energy saving achieved by thermal renovation measures were investigated to determine which energy saving measure is the most effective. Next, the magnitude of the energy saving gap was investigated, for different renovation measures. Finally, a logistic regression was executed to determine the probability of lower-than-expected-energy savings after a thermal renovation.

As this study progressed, it became clear that both the occupant and building characteristics influence residential energy consumption. However, the magnitude remained unclear and because significant variances in energy consumption among similar buildings were found, the influence of occupants and the technical characteristics on these variances were studied (see chapter 4). This is done by comparing the actual energy consumption of two different years for a group of houses retaining the same occupants with a group of houses with changing occupants over those years. This was the only study in which we had access to actual energy consumption data from both the Netherlands and Denmark.

Because both the occupant and building characteristics influence residential energy consumption and their influence is not only direct but also via interaction effects, it became clear that improving the theoretical energy consumption on the individual level without requiring more detailed input data is impossible. However, more detailed data is often not available, especially not on a large scale. Therefore, it seemed reasonable to attempt to reduce the energy performance gap on a building stock level by adapting the assumptions in the calculation method. This is done by an automated calibration method. The calibration method was not applied on an individual building, which is normally the case, but was used on a group of houses (see chapter 5).

This chapter presents the conclusions and recommendations from this study. Section 6.2 presents an overview of the conclusions of the previously mentioned chapters. Section 6.3 presents the overall conclusion through answering the main research question. After this the limitations of this study are then discussed in section 6.4. This is followed up by section 6.5 which provides the recommendations for policy practice and further research. Lastly, some final remarks are provided in section 6.6.

6.2 Key questions

The main question of this study is "Can occupant and building characteristics provide better insight into the difference between theory and practice of buildings' energy consumption and is it possble to reduce the gap between theory and practice?" To answer the main question, four key questions are formulated, which are each highlighted in one chapter of this thesis. This section provides an overview of the answers on the key questions and their sub-questions. Together, they form the answer to the main research question, which will be presented in section 6.3.

6.2.1 Performance gaps in energy consumption – household groups and building characteristics

To achieve the main aim of this study, the second chapter of this thesis details how building characteristics and household groups provide better insights into actual and theoretical residential energy consumption. The research question that is answered for this part of the study follows:

Can analysing building characteristics and household groups provide better insight into the energy performance gap?

This is investigated by analysing a large database containing more than 1 million households with occupant and building characteristics, as well as theoretical and actual energy consumption data, on a dwelling level. In the analysis, the relationship between building characteristics and household groups with actual and simulated energy consumption is examined. To obtain more specific insights, a more detailed analysis was conducted on the houses in the highest and lowest 10% energy-consuming groups. In this comparison the distribution of occupant and building characteristics for the highest, lowest and average energy consuming groups were compared.

Before answering this research question, a literature review was carried out to determine what is already known about the energy performance gap for residential buildings. Many studies indicate that the main cause of the energy performance gap is differences in energy-related occupant behaviour (see sections 2.1 and 2.2 of chapter 2). Because actual energy-related occupant behaviour data is difficult to collect, many researchers (and also this study) base their studies on occupant characteristics instead of energy-related behaviour [6-11], which are found to have a relationship with energy related occupant behaviour but are easier to collect. The literature review shows that studying occupant characteristics is an effective way to investigate the influence of occupants on residential energy consumption. Although the literature shows that energy-related occupant behaviour is expected to be the main explanation of the energy performance gap, there are other aspects that could play a role, such as the simplifications and assumptions that are made for the calculation method. However, they are investigated less frequently in this context.

The energy performance gap of residential gas consumption

Because previous studies have shown that the energy performance gap varies considerably between different energy-efficiency categories (energy labels), an analysis was performed to determine if this was also the case for the SHAERE database. Similar to the results of Majcen et al. (2013) , Figure 6.1 indeed shows that energy-efficient buildings consume more energy than expected and energy-inefficient buildings consume less energy than expected.

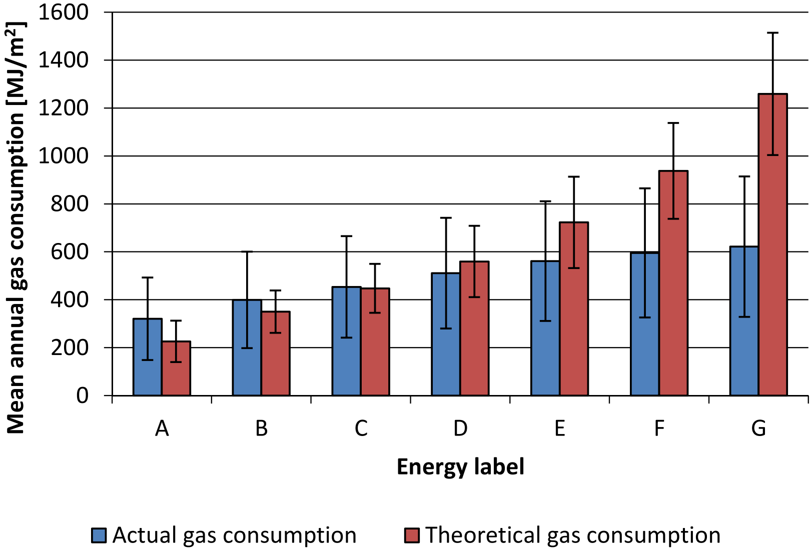

FIG. 6.1 Actual versus theoretical gas consumption per energy label based on data SHAERE database 2014

What is the relationship between the energy performance gap per household group concerning gas consumption?

To determine the relationship between the energy performance gap and household groups, 18 different household groups were generated, see Table 6.1, and compared for average actual energy consumption and the average energy performance gap.

TABLE 6.1 Household groups

	Household composition	Age (years)	Children	Age of children (years)	Work	Income
1	Single	≥65	No	n.a	Retired	n.a
2	Single	<65	No	n.a	State benefit	n.a
3	Single	<65	No	n.a	Employed	Low
4	Single	<65	No	n.a	Employed	Middle
5	Single	<65	No	n.a	Employed	High
6	Couple	>65	No	n.a	Retired	n.a
7	Couple	<65	No	n.a	State benefit	n.a
8	Couple	<65	No	n.a	Employed	Low
9	Couple	<65	No	n.a	Employed	Middle
10	Couple	<65	No	n.a	Employed	High
11	Family	<65	Yes	< 12	State benefit	n.a
12	Family	<65	Yes	< 12	Employed	Low
13	Family	<65	Yes	< 12	Employed	Middle
14	Family	<65	Yes	< 12	Employed	high
15	Family	<65	Yes	At least one > 12	State benefit	n.a
16	Family	<65	Yes	At least one > 12	Employed	Low
17	Family	<65	Yes	At least one > 12	Employed	Middle
18	Family	<65	Yes	At least one > 12	Employed	High

The analysis showed that single person households consume on average the least energy per square meter for heating and family households consume the most. The largest energy performance gap, however, is found for single-person households that received state benefits and the smallest is found for families with a high income. Because it was confirmed that the energy performance gap differs for each energy label category, the relationship between the energy performance gap per household group was investigated separately for each energy label category (see Figure 6.1). The results show that for the low-energy-efficient houses (labels D–G), family households have the smallest energy performance gap and for high-energy-efficient houses (labels A–C), single person households have the smallest gap. This indicates that there is no direct relationship between the performance gap and occupant characteristics or there are other factors that have a higher influence on the performance gap. Another explanation could be that the average energy-related household type behaviour is dependent on the energy efficiency of the dwelling, e.g. household types behave more energy efficiently in energy-inefficient than in energy-efficient dwellings (the pre-bound effect).

What can we tell about the highest and lowest gas-consuming groups?

To obtain a more detailed insight into the energy performance gap, the highest, average and lowest energy consumer groups are compared. Figure 6.2 and Figure 6.3 show the comparison for theoretical and actual energy consumption, respectively. The results clearly show that the differences between the groups are significantly higher for actual energy consumption compared to theoretical energy consumption. The figures also show that even the highest actual gas-consuming group consumes less gas than the predicted gas consumption. This indicates that the difference between low and high consuming groups is only partly dependent on building characteristics.

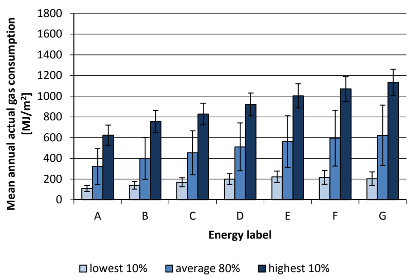

FIG. 6.2 comparing lowest, average and highest gas consuming groups theoretical consumption, based on data SHAERE and CBS database 2014

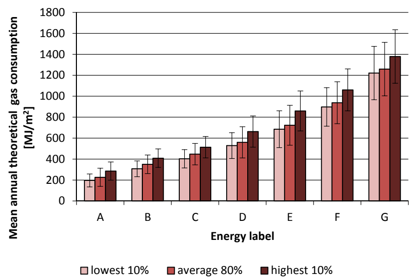

FIG. 6.3 comparing lowest, average and highest gas consuming groups actual consumption based on data SHAERE and CBS database 2014

To understand better why some households belong to a high-energy-consuming group and others to a low-energy-consuming group, the distribution of the groups are compared for different occupant and building characteristics. From these analyses, it can be concluded that occupant and building characteristics have a relationship with being placed in the low-, average- or high-energy-consuming group. For example, single-person households occur more often in the low-energy-consuming group and households with three or more members are more often found in the high-consuming group. In addition, households without children occur more frequently in the low-gas-consuming group. It was also found that low-income households occur more frequently in the extreme groups and high-income households occur more often in the average group. Employed occupants are more often placed in the low-energy-consuming group than unemployed occupants, this is independent from the energy energy label of the dwelling.

A closer look into the building characteristics show that single-family houses occur more often in the high-consuming group and apartments occur more often in the low-gas-consuming group. It was also found that houses with poor insulation occur more frequently in the high-energy-consuming group. An analysis also shows that the type of ventilation system is especially important for energy-efficient houses. For houses with energy labels F or G, the distribution does not differ significantly per group. Energy-efficient houses show (as expected) that balanced ventilation systems occur more frequently in the low-consuming group and natural ventilation systems are more often in the high-energy-consuming groups. The construction year of the building differs significantly for categories A, B and C. The results show clearly that older houses occur more frequently in the high-consuming group and more recently built houses occur more frequently in the low-consuming group. This indicates that even if buildings are renovated, it seems to be difficult to achieve the same performance as new-built houses.

The energy performance gap or residential electricity consumption

The energy performance gap of electricity consumption is easier to explain. The main cause of the gap is that in the calculation method, only building-related energy consumption is taken into account. This means that energy use for appliances and lighting (lighting is only considered building-related in utility buildings) are not taken into account. The results also show that the difference in electricity use between energy-efficient and energy-inefficient buildings is relatively small. This indicates that the use of electricity by occupants is not influenced by the energy efficiency state of their house. Further, the results show that the differences between household groups are significantly larger for actual electricity consumption compared to theoretical electricity consumption. Families with children older than age 12 consume the most electricity and single person households consume the least.

Conclusions

- The findings of this study show that analysing specific household types and building characteristics contributes to a better understanding of the influence of the occupant on actual energy consumption and the energy performance gap.
- The analysis of the consumers in the highest and lowest 10% energy-consuming groups can help policymakers choose the right target groups for their energy-saving policies and campaigns.
- The analysis showed that single person households consume the least energy per square meter for heating and family households consume the most.
- For low-energy-efficient houses (labels D–G), family households have the smallest energy performance gap and for high-energy-efficient houses (labels A–C), single person households have the smallest gap.
- The average highest 10% actual gas-consuming group consumes less gas than the lowest predicted gas-consuming group.
- Single-person households occur more often in the low-energy-consuming group and households with three or more members more often appear in the high-consuming-group.
- Households without children occur more frequently in the low-gas-consuming group.
- Low income households occur more frequently in the extreme groups and high-income households occur more often in the average group.
- Employed occupants occur more often in the low-energy-consuming group than unemployed occupants. This indicates that a higher occupancy time results in higher energy consumption.
- The type of ventilation system is especially important for energy efficient houses. For houses with energy labels F or G, the distribution does not differ significantly per group. Energy efficient houses show (as expected) that balanced ventilation systems occur more frequently in the low-consuming group and natural ventilation systems are found more often in the high-energy-consuming group.

- The construction year of the building differs significantly for categories A, B and C. The results clearly show that older houses occur more frequently in the high-consuming group and more recently built houses occur more frequently in the low-consuming group. This indicates that even if buildings are renovated, it seems to be difficult to achieve the same energy performance as new-built houses.

6.2.2 Actual energy-saving effects of thermal renovations in dwellings – longitudinal data analysis including building and occupant characteristics

Because the previous section showed that occupant and building characteristics significantly influence the energy performance gap, the next research question (presented in chapter 3 of this thesis) focusses on the main consequence of the energy performance gap: lower-than-expected energy savings after a thermal renovation. This study investigates the actual energy savings and the gap between actual and simulated energy savings for different types and combinations of thermal renovation measures. The research question that is answered in this study is:

Do occupant and building characteristics have a relationship with the difference between actual and theoretical energy savings after a thermal renovation?

This is investigated by analysing annual residential energy consumption data before and after the renovation of 90,000 houses in the Netherlands. Eleven renovation measures are identified to examine their relationship with building and occupant characteristics. Further, the probability that renovations result in lower-than-expected energy savings is investigated in research question. Also this question is answered by several sub questions, which are discussed below.

How frequently do thermal renovations result in lower-than-expected energy savings?

On average, 41% of the cases have higher energy savings than expected, 56% have savings that were lower than expected and only 3% of the renovations have well-predicted results (within 10% of the expected savings).

The descriptive statistics presented in chapter 3 also indicate that deep renovations most often result in lower energy savings than expected (82%). The same holds true for thermal renovations in which two or more insulation measures are applied. In 35% of the cases, the improvement of building installations results in higher-than-expected energy consumption. Regarding the single measures, we observed that improvement in the combined heating and hot water system and in façade insulation most often result in lower-than-expected energy savings.

Which thermal renovation measures result, on average, in the highest energy savings?

Figure 6.4 demonstrates (as expected) that most gas is saved when deep renovations are executed. The next highest energy-saving measures are improvements in installation systems (heating, hot water and ventilation systems) or a combi hot water and heating system, the insulation of the entire building envelope, the heating system, a change in windows, roof insulation, façade insulation, floor insulation and, finally, a ventilation and hot water system.

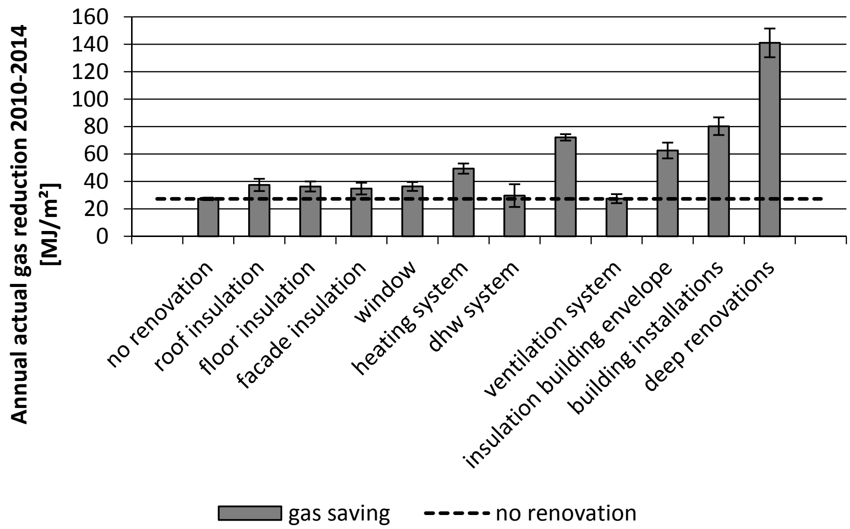

FIG. 6.4 Average energy saving per thermal renovation measure (including confidence interval 0.05), based on data SHAERE and CBS database 2010-2014
Note: Dashed line is actual difference in gas reduction between 2010–2014 for non-renovated houses.

Which thermal renovation measures result, on average, in the highest energy saving gap?

A comparison of the energy saving gap demonstrates that although deep renovations usually result in the highest energy savings, they also have the highest energy performance gap. In addition, the roof, façade, and entire envelope insulation have a relatively large energy performance gap if one compares this with their actual savings, whereas floor insulation saves more energy than expected (see Figure 6.5).

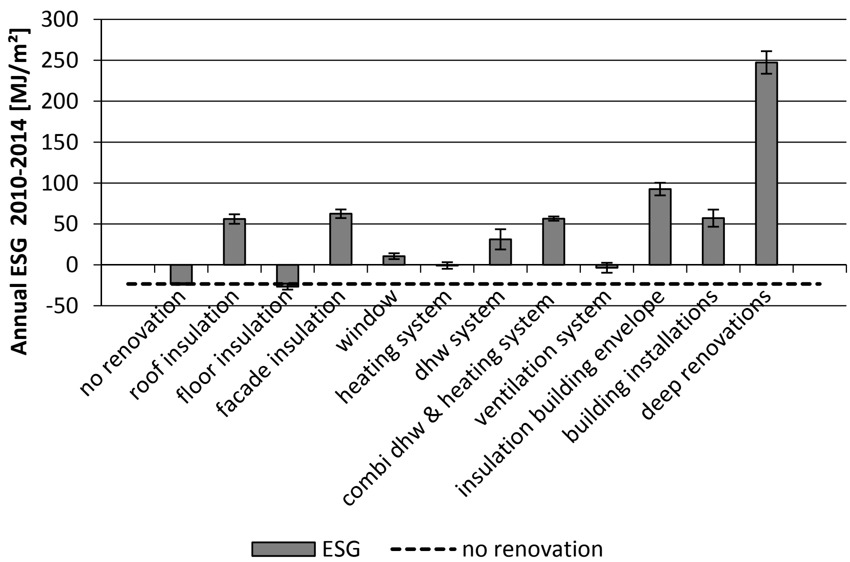

FIG. 6.5 Comparison of the annual energy performance gaps, based on data SHAERE and CBS database 2010-2014

Which factors have a relationship with the height of the actual energy savings after a thermal renovation?

There are several parameters found that influence the amount of energy saved after a thermal renovation. First, the energy savings per renovation measure is dependent on the energy-efficiency state of the building prior to the thermal renovation. Relatively energy-efficient houses benefit more from improved building installations, whereas relatively low-energy-efficient houses benefit more from improved insulation.

Second, on average, thermal renovations in single-family dwellings result in higher actual energy savings than multi-family dwellings. Energy renovation measures are often more effective on single-family houses than on multi-family houses because single-family houses have on average a relatively large building envelop, which highly influences energy use for heating.

Third, the results indicated that houses in which all adult members are employed have, on average, higher energy savings after building installation improvements than those in which not all adult members are employed. A possible explanation for this is that employed occupants might have more predictive occupancy patterns; therefore, the automatic control systems (for example, automatic thermostats) that often come with new building installations function better. However, this does not explain why the savings from hot tap water differ significantly. More research is needed to explain this phenomenon.

Households with a high income seem to save, on average, more energy after a thermal renovation compared to households with a low income. A possible explanation for this is that households with a low income are more willing to compromise on comfort to save energy and money in an energy inefficient house. After the renovation, less energy is needed to achieve the same comfort level; therefore, they can afford a higher comfort level, which results in lower energy savings. Another explanation is that households with a high income more frequently live in multi-family houses with larger building envelopes that have a high influence on the energy demand.

Which factors have a relationship with the energy performance gap after a thermal renovation?

There are several parameters that influence the amount of energy saved after a thermal renovation. For almost all thermal renovation measures, the energy-saving gap grows when the energy label is lower. This means that a renovation of a house with previously low energy-efficiency results in a larger gap between estimated and actual energy consumption.

The analysis also demonstrated that, on average, single-family dwellings save more energy than multi-family dwellings. Because the average savings per square meter is used, the average floor area is not an explanation for that phenomenon.

Only a few types of renovation show significant differences in the energy-saving gap between houses in which all adults work and those in which they do not. Most of those measures concern building installations (e.g., heating systems; DHW systems; combination DHW and heating systems; and ventilation systems).

In cases of overestimated energy savings (positive energy-saving gap), more households with an income below the national average income are noticed than those with a higher income, whereas the opposite holds true for measures with a negative energy-saving gap. This could indicate that people with a low income living in energy-inefficient dwellings are more willing to reduce their comfort levels in energy inefficient dwellings to save money than households with a high income.

Which parameters most influence the probability of lower-than expected energy savings?

At the end of chapter 3, the parameters that influence the probability of lower-than-expected energy savings were presented and it was found that 56% of the thermal renovations resulted in lower energy savings than expected. The binary logistic regression demonstrates that the employment status (all adult household members employed versus not all adult household members employed) and the energy performance gap before the thermal renovation significantly influence the probability of lower-than-expected energy savings. Because it is expected that the influence of the parameters differ for each renovation measure, the logistic regression is executed again with interaction effects. The results of the binary logistic regression with interaction effects show that the energy-efficiency state of the building before the renovation also has a significant influence on the probability of lower-than-expected energy savings; however, the influence differs for each renovation measure.

The building type also showed significant interaction effects, which means that the relationship of lower-than-expected energy savings with the building type also differs for each renovation measure.

Conclusions

- Deep renovation measures result in the highest energy savings but also in the highest energy-saving gap.
- The effectiveness of renovations is dependent on the state of the building prior to the thermal renovation.
- The effectiveness of renovations is partly dependent on the type of occupant who is living in the dwelling.
- Renovations of low-energy-efficient houses result, on average, in a larger energy-saving gap than high-energy-efficient houses.
- On average, single-family dwellings save more energy than multi-family dwellings after a thermal renovation.
- The amount of energy saved after a thermal renovation is dependent on the energy efficiency of the dwelling prior to the thermal renovation, type of dwelling, income level of household and employment status.
- Apart from deep renovations, it is impossible to conclude which thermal renovation measure is the most effective, because it is dependent on the energy efficiency of the building prior to the thermal renovations, the type of building, income level of occupants and occupancy time.
- Tailored thermal renovation advice is required to decide on the most effective thermal renovation measure.

6.2.3 Variances in residential heating consumption – importance of building characteristics and occupants analysed by movers and stayers

The previous research questions showed that occupants and building characteristics both have a significant influence on buildings' energy consumption. However, the magnitude is unclear and because many people assume that the energy performance gap is completely caused by differences of occupants, an analysis of the variances in actual energy consumption was conducted to determine to what extent occupants and building characteristics influence this variance (see chapter 4). The research question that is answered in this study is:

To what extent are occupants and building characteristics responsible for the variances in actual residential energy consumption?

This research question is answered by analysing about 370,000 non-renovated houses from the Netherlands and about 510,000 houses from Denmark between the years 2010-2015. This comparative design enables a stronger generalisability of the results, which is seldom seen in quantitative energy consumption studies. The actual annual energy consumptions of houses with the same occupant and houses with different occupants over the years were compared. Using this method we did not only investigate different occupant characteristics (like the previous two research questions) but we studied the influence of the occupant on residential energy consumption in general. The question is answered by sub-questions that are explained below.

To what extent are occupants and building characteristics responsible for the variances in actual residential energy consumption on a national level?

As shown in Figure 6.5, approximately half of the variation in residential heat can be ascribed to differences between buildings and the other half to the occupant. Variations in residential heating consumption across the years of Dutch social housing can be explained by occupants (49%), by the Dutch energy simulation model (theoretical consumption) (20%), and by other physical characteristics that are not taken into account in the building simulation model (32%). For the Danish case, 48% of the variation in residential heating consumption can be explained by occupants, 27% by the building and 25% by other physical characteristics (see Figure 6.6).

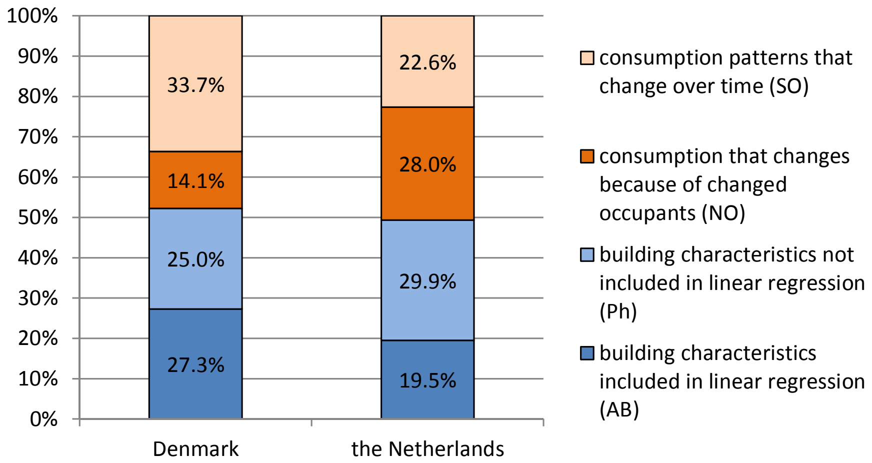

FIG. 6.6 Comparison of the influence of building characteristics and occupants on the variances in energy consumption – Denmark and the Netherlands, based on SHAERE and CBS database 2010-2015 for the Netherlands and Building and Dwelling Register (BBR), the Danish Ministry of Taxation 2010-2015 for Denmark

Is the influence different for different energy labels?

Executing the same analysis for each energy label shows that occupants have more influence percentage-wise on the variance of energy-efficient houses than on energy-inefficient houses. An analysis of the construction year confirms the previous results in the analysis of the energy labels.

Is the influence different for different building types?

The analysis indicates that occupants explain a higher percentage of the variance for multi-family houses than for single-family houses. A possible explanation for this could be that small changes in consumption patterns are more effective in multi-family houses than in single-family houses because of the relatively smaller floor area of those dwellings. For example, opening a window in a small room will have more effect on the thermal climate than opening a window of a similar size in a larger room.

Is the influence different for different ventilation systems?

The comparison of the three different ventilation systems (natural ventilation, natural inlet and mechanical exhaust, and balance ventilation with heat recovery) indicates that the influence of the occupant is higher for houses with a balanced ventilation system compared to houses with a natural or natural inlet mechanical exhaust ventilation system. This is expected, because houses with a balanced ventilation system often make use of heat recovery systems. To make optimal use of such a system, all air that enters and leaves the building should go through this system. However, occupants are still able to open windows. Opening the windows means the air does not pass the heat recovery system, which will lead to extra heat losses. Opening windows when a heat recovery system is installed will therefore have a more significant effect than in houses in which no heat recovery system is installed. Further, balanced ventilation systems are primarily installed in energy-efficient buildings.

Is the influence different for different heating system?

Finally, we compared the heating systems. Because of the differences in the databases, the categories we compared are different for the Dutch and Danish cases. For the Dutch case, we compared different gas heating systems. The results of the Dutch case show (contrary to previous findings) that relatively energy-efficient installations are less sensitive to energy-related occupant behaviour than energy-inefficient systems. However, the differences between boilers are relatively low, although the distribution of local gas heaters is an exception. This is interesting because the operation of boiler systems are more or less the same, but the local gas heaters have a different operating system. Therefore, these results could indicate that different operation systems cause differences in energy-related behaviour. For the Danish case, a comparison was made between houses with gas heating and with district heating systems. These results indicate that the share of consumption that changes because of changed occupants is lower for houses with a district heating system compared to houses that are heated by gas.

Conclusions

- Approximately half of the variation in residential heating consumption can be ascribed to differences between buildings and the other half to differences in energy-related occupant behaviour.

- Variations in residential heating consumption across the years of Dutch sample can be explained by occupants (49%), the Dutch energy simulation model (theoretical consumption) (20%), and by other physical characteristics that are not taken into account in the building simulation model (32%).

- For the Danish case, 48% of the variation in residential heating consumption can be explained by occupants, 27% by the building characteristics and 25% by other physical characteristics.

- The influences of the occupant on variances in energy consumption are dependent on the building characteristics.

- The influence of occupants is larger for energy-efficient houses than for energy-inefficient houses.

- The influence of occupants is dependent on the type of building installations in the house.

- There is still a relatively large number of physical characteristics that cause variances in heating consumption that are not (correctly) taken into account in the theoretical energy calculation.

6.2.4 Calibration of energy simulation models on a building stock level using actual energy consumption data

Based on the results of the previously described studies we can conclude that it is impossible to predict residential energy consumption accurately on an individual level without having both occupant and building characteristics data. However, it is expected that on an aggregated level the predictions can be improved. Accurate prediction models on a dwelling stock level are important for policymakers, strategy developers and others. Therefore, the research question of the fourth part of this thesis is:

Is it possible to reduce the energy performance gap on a building stock level?

This research question is answered by developing a method that aims to reduce the average energy performance gap. To develop this method several sub-questions are answered.

Is the energy performance gap present in both steady state and dynamic simulation models?

The results of chapter 5 show that if the same level of information is known, the energy performance gap is indeed present for both the steady state and dynamic simulation model. Also the magnitude of the gap is comparable (See Figure 6.7 and Figure 6.8).

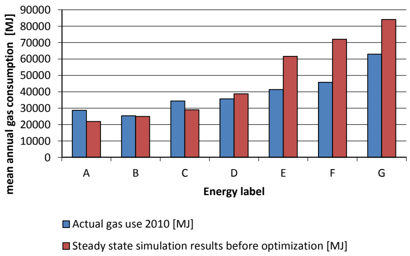

FIG. 6.7 comparison actual versus simulated gas consumption (calculated with steady state method), based on data from WoON energiemodule 2012)

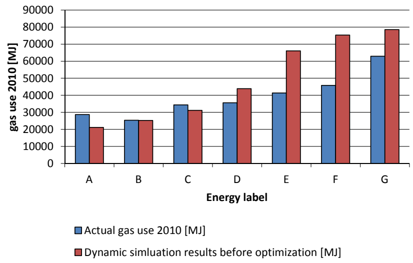

FIG. 6.8 comparison actual versus simulated gas consumption (calculated with dynamic method) , based on data from WoON energiemodule 2012

How can we improve the assumptions in simulation models?

An optimisation method is used to reduce the Root Mean Square Error of a sub sample of dwellings by adapting the assumptions that are used in the model. Because the optimised sample is representative,the optimised parameters can be used to predict residential energy consumption of other buildings, which makes existing simulation tools a more reliable tool. The effectiveness of the method is tested on a control group. The proposed method is inspired by traditional automated calibration methods, however instead of matching a detailed simulated energy consumption pattern with a detailed actual energy consumption pattern on an individual building level, the proposed method aims to match simulated annual energy consumption of multiple houses with actual annual energy consumption data at the same time. The proposed method contains 11 steps (Figure 6.9).

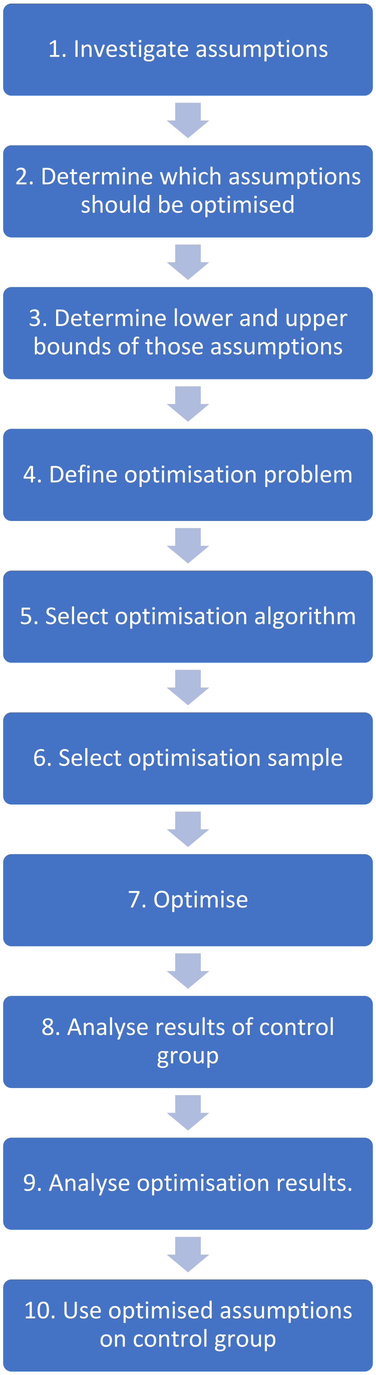

FIG. 6.9 Stepwise method description

Which assumptions are made in building simulation models?

For every building simulation model assumptions are made. For simplicity reasons we do not describe all possible assumptions that can/have to be taken in building simulation models. Instead we limited ourselves to the assumptions that are taken in the calculation method of the Dutch energy label and energy index (ISSO 82.3) [12]. If possible the building characteristics are defined by visual inspection, otherwise assumptions are made. If the Rc-value of the façade is unknown, an assumption for this value is made based on construction period. The same is done for the assumptions of the Rc value of the floor and roof. Another assumption that often is made is the ventilation rate. In the ISSO 83.2 method that we studied, the ventilation rate is based on floor area and type of ventilation system. Infiltration rate is based on floor area and type of building. The average indoor temperature is assumed to be the same for every building (18°C). The assumed use of domestic hot water is based on number of occupants, which is based on the floor area category of the dwelling. Furthermore, there are efficiencies of the heating system and domestic hot water systems which are based on the equipment details provided by the manufacturer. For simplicity reasons in the case studies we used to prove the effectiveness of the method, only the thermal insulation of the wall, the amount of domestic hot water use, indoor temperature and the air change rate are optimised.

What are the boundary conditions?

The assumptions for the R_c values in the Dutch energy labelling method are based on requirements of the Dutch building code at the time of construction. For the lower bound the assumed R_c value of the previous category is chosen and for the upper bound the value of the next category is chosen. Because the values of the first two categories (before 1965 and between 1965 – 1975) lay close together, they have the same lower bound. Also, the values of the last two categories (between 1988 - 1992 and after 1992) lay relatively close to each other. Therefore, for those cases higher upper bounds are chosen. The air change rate in the building is dependent on a combination of infiltration and type of ventilation system. For the ventilation system an upper bound of 200% and a lower bound of -90% of the initial assumption are chosen. For the amount of domestic hot water use, as a lower bound the average amount of water for one person is chosen and as an upper bound the average amount of water for five persons is chosen. The indoor temperature is assumed to have a maximum of 25 ^{o}C and a minimum of 14 ^{o}C.

Which optimisation algorithm should be used?

The choice of the most effective optimisation algorithm for a certain optimisation problem is difficult to determine in advance of the optimisation. The only way to be certain about the most optimal optimisation choice is to try multiple algorithms. However, this is time consuming and defeats the purpose of finding the minimum. Although determining the most efficient algorithm is not possible without trying multiple methods, an educated guess can be made by analysing the optimisation problem and optimisation studies done in the past. For the optimisation problem in this study, two optimisation algorithms are chosen. For the dynamic simulation model the surrogate optimisation model of Matlab is chosen. This model first tries multiple random options. Based on the results of those trials a surrogate model is conducted which helps the algorithm to choose the next best guess. Because the computation of the surrogate model also requires some computation time, this method is only efficient if the optimisation problem is computational intensive; this is the case for the dynamic simulation model. The steady state simulation model is significantly less time consuming and therefore another optimisation algorithm might be more effective. For this optimisation model the particle swarm method is chosen. This algorithm has shown in previous studies to be, in a majority of the cases, more efficient than the other available algorithms (e.g. Genetic Algorithm, Pattern search).

Does an improvement of assumptions solve the energy performance gap?

The research shows that the method indeed reduces the energy performance gap significantly for both the steady state and dynamic simulation method (see Figure 6.10-6.13). By applying the method, a reduction of the Root Mean Square Error of 20-25% was achieved and the R^2 of a linear regression between actual and simulated energy consumption improved with 8-11%. The main outcomes of the optimisation are: that the average indoor temperature should be assumed significantly lower compared to the current assumption; the insulation rates of the older buildings should be assumed higher than currently assumed. Currently the ventilation rates for naturally ventilated dwellings and for dwellings with a mechanical exhaust ventilation system are assumed the same, however the optimisation shows that naturally ventilated homes have a lower ventilation rate than dwellings with a mechanical exhaust ventilation system. For domestic hot water we found that the defined floor area categories are likely not yet optimal. For the smallest dwelling category we found that the assumed amount of domestic hot water should be higher, while the assumed value for dwellings in the second size category should be a bit lower. This means that on average the domestic hot water consumption of those two categories lay closer together than assumed.

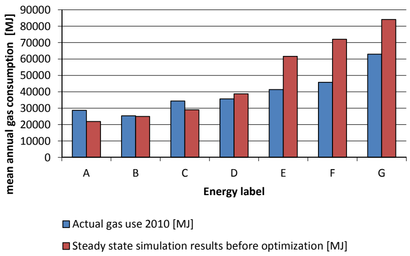

FIG. 6.10 comparison actual versus simulated gas consumption before optimisation (calculated with steady state simualtion method) , based on data based on data from WoON energiemodule 2012

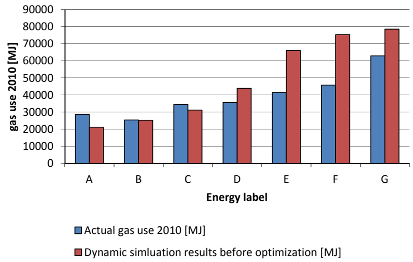

FIG. 6.11 comparison actual versus simulated gas consumption before optimisation (calculated with dynamic simulation method) , based on data from WoON energiemodule 2012

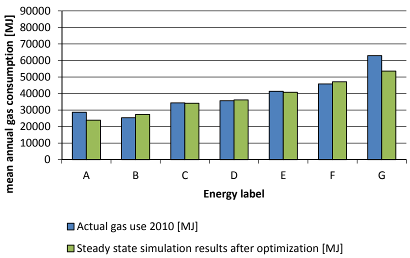

FIG. 6.12 comparison actual versus simulated gas consumption after optimisation (calculated with steady state simulation method) , based on data based on data from WoON energiemodule 2012

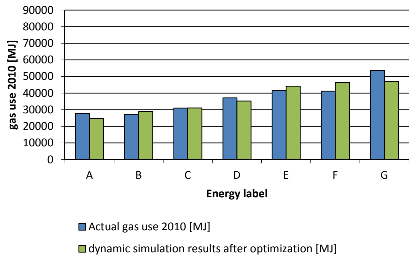

FIG. 6.13 comparison actual versus simulated gas consumption after optimisation (calculated with dynamic simualtion method) , based on data from WoON energiemodule 2012

Conclusions

- There is an energy performance gap for both steady state and dynamic simulation models and the magnitude of this gap is similar.
- The optimisation sample should be representative for the entire sample but should also contain enough cases per parameter that will be optimised.

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- The most important assumptions to optimise are indoor temperature, insulation rate of façade (floor and roof if present), ventilation and infiltration rate and the amount of domestic hot water use

- To reduce the energy performance gap an optimisation method can be applied which aims to reduce the Root Mean Square Error by adapting the assumptions of the simulation method within certain boundary conditions.

- The proposed optimisation method indeed reduces the energy performance gap significantly. The Root Mean Square error is reduced with 20-25% and the R^2 of a linear regression between actual and theoretical annual energy consumption increases with 8-12% Which indicates that the optimised parameters settings indeed result in a better prediction of residential energy consumption.

- More research should be done towards the physical meaning of the optimisation results and the practicle applicability.

6.3 Overall conclusion

The answers to the research questions presented in the previous section result in an overall conclusion to the main research question:

Can occupant and building characteristics provide better insights into the difference between theory and practice in residential energy consumption, and is it possible to reduce this difference?

This thesis results in two main conclusions. First, both occupants and building characteristics have a significant relationship with the gap between theory and practice in residential energy consumption and saving. Second, it is impossible to reduce the energy performance gap on an individual level without using more detailed data than the buildings simulation tools that the Dutch government currently uses and is planning to use in 2020. However, reducing the average energy performance gap on a building stock level is possible by adapting the assumptions used in building energy simulation models.

In the first part of this study, we investigated the influence of building and occupant characteristics on the energy performance gap. This was followed by an investigation of the gap between predicted and actual energy saving after a thermal renovation. Both show that not only occupants but also the building characteristics play an important role in the difference between theory and practice. An analysis of the variances in actual energy consumption through comparing consumption over the years of houses with the same occupants and houses with changed occupants showed that occupants are currently responsible for almost 50% of the variance and building characteristics for the other 50%.

All of these findings together prove that it is important to continue analysing actual energy consumption to determine real-life home energy use. The results show that the relationships between building and occupant characteristics and actual energy consumption are very complex and therefore difficult – and perhaps impossible – to incorporate in traditional physical building simulation models. The results point to the possibility that conventional physical building simulation models should be completed with data-driven models that make use of e.g. machine learning techniques.

A first step using optimisation algorithms/machine learning techniques and actual energy consumption data in building simulation models was shown in chapter 5 of this thesis. This chapter showed that it is possible to reduce the average energy performance gap significantly by optimising the parameter settings used in the assumptions in the simulation model by using actual energy consumption data of multiple dwellings. The use of optimisation algorithms on multiple buildings, help to improve the assumptions for the simulation method, which reduces the energy performance gap and make the outcomes a more reliable tool. A better reliability of building energy simulations is crucial for (amongst others) policymakers and practitioners to make the right decision regarding energy renovations, subsidies, energy saving targets, and energy saving policies in the built environment.

6.4 Data quality and limitations

6.4.1 Gas consumption for space heating

In this study, residential energy consumption is defined as households' energy use for various indoor purposes: space and water heating, space cooling, cooking, lighting and electrical appliances. In the Netherlands, residential energy consumption has a significant influence on the total energy consumption. The majority of residential energy consumption in the Netherlands is used for space heating, but a significant amount of residential energy consumption is used for domestic hot water and lighting and appliances (Figure 6.14). Energy demand for cooking and space cooling have a negligible (average 2.2%) influence on the total Dutch residential energy consumption and are therefore not taken into account in this study.

Because the majority of the Dutch residential energy consumption is used for space heating and previous studies have indicated that the energy performance gap for space heating is much more difficult to explain than the energy performance gap for lighting and appliances, the main focus in this study is on the energy performance gap as it relates to space heating [17]. Because the vast majority of Dutch households (90%) use gas as a heating source for space heating , the difference in actual and simulated gas consumption was used to define this energy performance gap. This implies that houses that use electricity or district heating as the main heating source are not taken into consideration. There are, in the Netherlands, often highly energy efficient heating systems (heat pumps and cogeneration) in energy efficient houses, but there are also some inefficient houses that use electrical radiators.

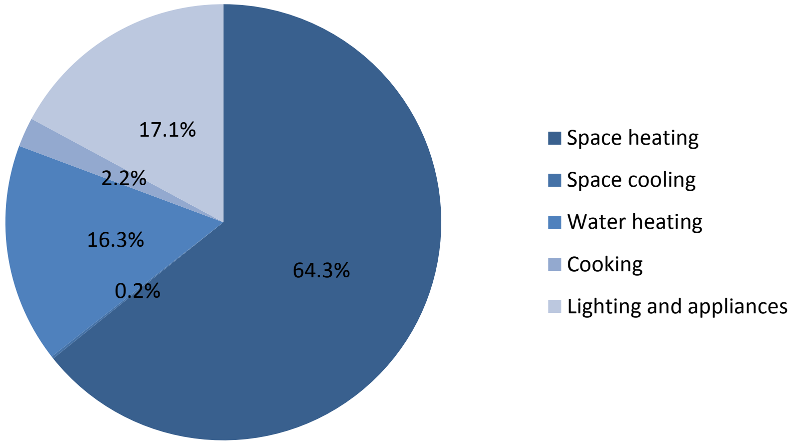

FIG. 6.14 Residential energy consumption in the Netherlands(Eurostat 2017 [17])

6.4.2 SHAERE database

The representativeness of the data also forms a possible limitation of the research. To answer the first three research questions, the SHAERE database is used, which contains only houses from social housing companies. This means that there is a bias in ownership. Although the Dutch social housing sector mainly provides houses for people with a relatively low income, there were also houses with occupants with a relatively high income. This makes it acceptable to use the SHAERE database, which provides great benefits, as it is the largest available database in the Netherlands on a detailed level (on average, more than 1 million houses per year). Additionally, social housing companies that deliver their data to the SHAERE database are required to do so every year. This means that there are records for several years for each house, which makes it possible to follow the development not only of the social housing stock but also of individual houses, tracking the effect of thermal renovations. This also means that any data provider mistakes will not have a significant influence on the overall analysis.

6.4.3 Danish data

In the fourth chapter not only the SHAERE and Statistics Netherlands databases are used, but also two Danish databases are used. Those databases are similar to the Statistics Netherlands and SHAERE databases. However, unlike the SHAERE database, the Danish database only contains owner-occupied houses. This could cause possible bias, however, the majority of the Danish housing stock is owner-occupied and therefore it is believed that the research results will not be influenced significantly.

6.4.4 WoON database

The fifth chapter uses the WoON database. This database was used because the protected Statistics Netherlands environment for microdata did not allow for the possibility to conduct an optimisation. The main problem of the WoON database is that not all building characteristics that are needed for the energy label calculation are incorporated in the database. For example, only the orientation of the living room is given but not the orientation of all windows. According to the documentation for the missing data, some assumptions were made but the owner of the database was not able to determine what those assumptions were. This made it difficult to build a simulation model that represented the theoretical energy consumption as presented in the database. However, the results of the research presented in chapter 5 indicate that the method used is suitable to reduce the energy performance gap.

6.4.5 Theoretical energy consumption

This study compares actual and simulated energy consumption; however, there are several ways to simulate energy consumption, some more accurate than others. This study primarily used simulated energy consumption based on the calculation method ISSO 82[12], which is also the method used for the EPCB. It should be mentioned that this method is a very simplified reflection of reality, based on a quasi-steady-state calculation method. Nevertheless, this method was used because it is the basis for many energy-saving policies and monitoring systems. In addition, many researchers have shown that if one compares the annual energy demand results of steady-state simulation methods with dynamic simulation methods, the results will not differ significantly [13]. This was also shown in chapter 5 of this dissertation. Additionally, for dynamic simulation methods to be more accurate, more detailed information is required, which is often not available.

6.4.6 Correcting actual energy consumption

To make the actual energy consumption comparable with the theoretical energy consumption, it has been corrected for degree days (see chapters 2, 3 and 5). However, previous studies have shown that this method is not perfect [14, 15]. For example, it is expected that occupants in low-insulated houses will use their heating system more often than occupants in a highly insulated house. Therefore, the correction could lead to a overestimation of actual energy consumption.

6.5 Recommendations

This study showed that residential energy consumption, along with the energy performance gap, is dependent on numerous different parameters that occur in endless possible combinations. This implies that it is almost impossible to predict energy consumption on an individual dwelling level if only building characteristics are known, mainly because interaction effects make their relationship complex. However, this study showed that with the use of actual energy consumption data and optimisation techniques, the energy prediction models can be improved on a building stock level without changing the calculation method or adding extra information into the model. This study also proves the importance of monitoring and the availability of actual energy consumption, occupant and building characteristics data. Based on the research results, recommendations can be made in three categories: policy, practice and future research.

6.5.1 Recommendations for policy

Theoretical energy consumption results from the Dutch energy label method are widely used by policymakers. They are used to monitor the energy efficiency state of the Dutch building stock, increase awareness, determine which actions are needed to achieve the desired energy-saving targets, assess the progress of energy-saving policies, and award subsidies. However, the energy-saving targets that should be reached are related to actual energy consumption. Because there is a significant mismatch between theoretical energy consumption and consumption in practice, energy saving policies often do not achieve the desired results.

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The first recommendation to policymakers is that one should always be aware that the theoretical energy consumption from this method does not aim to predict residential energy consumption accurately. If the theoretical energy consumption results of this calculation are used, it should be taken into account how they could differ and what the consequences are for their policies. This study, along with previous studies by Guerra Santin [9], and Filippidou [16], provide significant information that will help to understand the potential risks of using theoretical energy consumption.

Second, policymakers should be aware that the energy performance gap exists on two different levels. The first is the housing stock level. This discrepancy causes problems when the method is used to monitor the energy savings from building renovations of Dutch building stock, determine which actions are needed to achieve the desired energy-saving targets, and assess the progress of energy-saving policies. This study presents a method to reduce the gap on a building stock level by changing the assumptions in the calculation method. Chapter 4 demonstrated that the influence of occupants varies for different building characteristics (see chapter 4). Because the housing stock and its characteristics change, this suggests that the assumptions should be calibrated on a regular basis to minimize the energy performance gap in the long run. To achieve higher energy savings, policymakers could make use of the results in, for example, chapters 2 and 3. The second chapter discusses the characteristics of the highest and lowest energy-saving groups and the third chapter shows the average energy savings for each renovation measure.

The second level in which the energy performance gap is also a problem is on an individual dwelling level. Subsidies are for example awarded based on the number of label steps that the building improves after renovation. However, chapter 2 showed us that there are also differences within each label category (see chapter 2), which means that not necessarily the most efficient renovation measure will be chosen if one is only focussed on improving the energy label of a building. Further, not all renovation measures are as effective, although they result in higher energy efficiency on paper (see chapter 3). For example, a more energy-efficient hot tap water system often results in higher energy consumption. Chapter 3 also showed that the magnitude of the energy performance gap prior to the renovation plays an important role in the probability of having lower energy savings than expected. Therefore, it might be better to look at the current energy bill, energy-related occupant behaviour and building characteristics to determine which energy-saving measures are the most effective and make a more realistic estimation of the amount of the subsidy that should be granted. This may be time-consuming but results from this study indicate that it should be possible to construct models that make use of real energy consumption data, which can help provide more useful guidance.

This study also demonstrated the importance of the availability of data. Real energy consumption and building and occupant characteristics data are of importance in obtaining insight into the actual effectiveness of energy renovations and the energy performance of the housing stock. This study shows that the energy-performance and energy-saving gaps are dependent on occupants and building characteristics. Due to the most recent energy transition plans, the characteristics of the housing stock will change significantly; in addition, occupant characteristics are changing over time (for example, there are currently significantly more one-person households than in the past). This implies that constant monitoring is needed. The energy transition will require extra monitoring as new systems are introduced and it is important to monitor whether these systems indeed result in the requested energy savings.

Another important aspect that should be considered is that the energy transition will result in significantly more houses heated by electricity and district heating systems. Currently, we were able to distinguish energy use for heating and domestic hot water by analysing gas consumption because most houses in the study use gas as a heating source. Data of energy use for district heating is considered unreliable according to Statistics Netherlands and electricity consumption data is mixed with energy use for appliances. This makes the analysis and monitoring process of actual energy consumption significantly more difficult and it is therefore advisable to take this into account and find solutions for this problem.

A new energy label calculation method will be introduced in 2020 (NTA 8088). It is recommended that, as soon as possible, policymakers get an understanding of how this method relates to the previous methods for the energy labels and to actual energy consumption. It is also recommended that when new calculation methods are introduced, conversion methods are developed to ensure that databases from previous years will remain usable. In the NTA 8088 the Energy Index (which is a non-dimensional number that should reflect the energy performance of a building) is replaced by a theoretical energy consumption number in kwh/m^2. This will tempt people even more to use theoretical energy consumption for for example predictions of energy savings, setting energy saving targets , which will make it even more important that the gap between actual and theoretical energy consumption will be as small as possible.

6.5.2 Recommendations for practice

To determine potential energy savings, one should take the current energy consumption and energy-related occupant behaviour into account. Results also show that the effects of some energy saving methods are smaller than others. Before renovation, one should be aware of this. The results of this research could be used to determine the probability of lower-than-expected energy saving effects after a thermal renovation and the results give a suggestion which aspects are important to take into account by making the decision for the most effective energy saving measure. However, because every situation is unique, tailored advice remains important.

This study demonstrated that a renovated house with energy label A consumes, on average, significantly more energy than a newly built house with energy label A. This could indicate that mistakes or shortcuts in the renovation process were made; for example, re-insulating an old building that is not perfectly straight like a new building is often more difficult and time consuming, which may provoke hurried, poor-quality work. Therefore, it is recommended to pay extra attention that renovations of older houses are executed as required.

Further, it was proven that it is most efficient to start with the reduction of residential energy consumption. This shows that one should start by increasing the insulation level of the building envelope and, only when this is optimised, put effort in installing more energy efficient building installations (see chapter 3).

The results also show that the most effective renovation measure depends on the current state of the dwelling and how the dwelling is used. Therefore, the most effective measure differs for each household. Tailored advice is needed to determine the most effective method for a specific case (see chapter 3).

One should also realise that if reducing energy consumption is the only aim of a thermal renovation and the payback time has to be as short as possible, an increase in comfort level can then not be demanded. For example, this study showed that the change of a local gas stove into a condensing gas boiler often results in an increase in energy usage. This is likely because of an increase in the comfort level in the house. Therefore, one should take into account that, although some building installations are presented as energy-saving measures, they only reduce consumption if the comfort level (and sometimes) in the house remains the same as before the renovation measure. However, in reality this is often not desirable. This should be explained in advance of the renovation to the occupants and/or home owner to prevent unrealistic expectations of energy savings.

6.5.3 Recommendations for future research

Although this study examined many aspects, consequences and solutions for the energy performance gap, there is still much to be done to solve the problems of this gap. In addition, the current developments within the energy transition require further study.

First, practice shows that there is a need for simple simulation models that can be used to monitor the energy-efficiency state of the building stock, determine which actions are needed to achieve the energy-saving goals, and decide how much of a subsidy can be granted. Currently, the theoretical energy consumption results of the energy label calculation are often used for this purpose. However, the energy performance gap of this method makes it unsuitable. This study showed that the gap can be decreased using calibration techniques on a building stock level. However, we only tested a limited amount of assumptions and building types. For further development of this method it is recommendable that the optimisation method is applied on a larger sample with more parameters that have to be optimised. Further, for predicting energy consumption on an individual level, this study showed that actual energy consumption, building characteristics and occupant data can provide better insights into the energy performance gap. The results are, however, not yet incorporated in easy-to-use models, but they show potential for this. Therefore, it is recommended that future studies should focus on how to use actual energy, occupant and building data in easy-to-use models that fairly accurately predict actual energy consumption on both an individual and building stock level.

Second, the ongoing energy transition in the Netherlands aims for a housing stock that does not use natural gas. This study examined only houses with natural gas as a heating source. Because currently 85% of the houses in the Netherlands use natural gas as a heating source, this does not cause bias. The change from gas to electric, district heating or possibly hydrogen will significantly change the characteristics of the building stock and, in turn, the actual energy consumption and energy performance gap. Monitoring the effectiveness of these measures is important because this transition aims to reduce CO_2 emissions and energy consumption. One should also investigate how to deal with the lack of reliable energy consumption data for houses on district heating systems and the issue that all-electric houses' actual energy data are a combination of energy use for heating, domestic hot water, appliances and lighting.

Third, there are other aspects that influence the energy performance gap that were not taken into account in this study but should be considered in the future. Although some of the research results indicate that there might also be problems in the construction process that influence the magnitude of the energy performance gap, this study did not investigate this. Further studies should investigate to what extent this aspect influences the energy performance gap. In addition, mistakes in the building inspection process could influence the gap but are not investigated in this study.

Finally, costs are not taken into account in this study. This study only focusses on the actual savings and examines how to achieve the highest energy savings; however, in practice, energy renovation decisions are often based on cost. Therefore, we recommend that, apart from energy-efficiency research and energy prediction models, the costs of certain measures are taken into consideration in future studies. Having both available would allow for a more well-rounded perspective in making informed choices of building energy renovation measures.

6.6 Final remarks

The aim of this study was to determine the relationship between building and occupant characteristics and the gap between theory and practice of residential energy consumption, as well as to reduce the energy performance gap. This is investigated by analysing large databases that contain actual and theoretical energy consumption, occupant and building characteristics data. The study presented the relationships between occupant and building characteristics and the energy-performance and energy-saving gaps. Further, the study demonstrated the influence of building characteristics and occupants on actual residential energy consumption. Finally, a method to reduce the energy performance gap on a building stock level by using actual energy consumption data was introduced. The results show that reducing the performance gap on individual level can be accomplished by adding more detailed occupant characteristics and behaviour data, the reduction on an aggregated level can be accomplished by changing the assumptions in the calculation method. Although this thesis is mainly based on Dutch data, this thesis does not only provide valuable insights for the national but also for the international research community, because the problem of the energy performance gap exists in any country that uses theoretical energy consumption for policy making, design decision making and the calculation of payback times of energy renovations. The thesis shows the importance of the energy performance gap, the importance of monitoring actual energy consumption data; and a first step towards the use of machine learning techniques in combination with actual energy consumption data and building energy simulation models. Based on the results of this research it is expected that the solution of the energy performance gap and therewith the reliability of building energy simulation models lays in a combination of actual energy consumption data, statistical and machine learning techniques and existing building energy simulation techniques.

References

[1] Sutherlands, G., P.G. Audi, and A. Lacourt, *2016 Implementing the Energy Performance of Buildign directive (EPBD) featuring country reports*. Concerted action - Energy Performance of Buildings, ed. E. Maldonado. 2015, Portugal: European Union.

[2] Dascalaki, E.G., et al., *Data collection and analysis of the building stock and its energy performance—An example for Hellenic buildings*. Energy and Buildings, 2010. **42**(8): p. 1231-1237.

[3] Hamilton, I.G., et al., *Energy efficiency in the British housing stock: Energy demand and the Homes Energy Efficiency Database*. Energy Policy, 2013. **60**: p. 462-480.

[4] Filippidou, F., N. Nieboer, and H. Visscher, *Are we moving fast enough? The energy renovation rate of the Dutch non-profit housing using the national energy labelling database*. Energy Policy, 2017. **109**(Supplement C): p. 488-498.

[5] Filippidou, F., N.E.T. Nieboer, and H. Visscher, *Effectiveness of energy renovations: a reassessment based on actual consumption savings*, in *eceee*. 2017: France.

[6] Druckman, A. and T. Jackson, *Household energy consumption in the UK: A highly geographically and socio-economically disaggregated model*. Energy Policy, 2008. **36**(8): p. 3167-3182.

[7] Brounen, D., N. Kok, and J.M. Quigley, *Residential energy use and conservation: Economics and demographics*. European Economic Review, 2012. **2012**(56): p. 931-945.

[8] Guerra Santin, O., L. Itard, and H. Visscher, *The effect of occupancy and building characteristics on energy use for space and water heating in Dutch residential stock*. Energy and Buildings, 2009. **41**(11): p. 1223-1232.

[9] Guerra Santin, O., *Actual energy consumption in dwellings; the effect of energy performance regulations and occupant behaviour*. OTB, ed. S.U. Areas. 2010, Delft: TU Delft. 237.

[10] Steemers, K. and G.Y. Yun, *Household energy consumption: a study of the role of occupants*. Building Research & Information, 2009. **37**(5-6): p. 625-637.

[11] Yohanis, Y.G., *Domestic energy use and householders' energy behaviour*. Energy policy, 2011. **41**(2012).

[12] ISSO, *Energieprestatie advies woningen*, in *82.3*, ISSO, Editor. 2011: Rotterdam.

[13] Van der Veken, J., et al., *Comparision of Steady-state and dynamic building energy simulation programs*, in *ASHRAE Buildings IX*, ASHRAE, Editor. 2004, ASHRAE: unknown.

[14] Azevedo, J.A., L. Chapman, and C.L. Muller, *Critique and suggested modifications of the degree days methodology to enable long-term electricity consumption assessments: a case study in Birmingham, UK*. Meteorological Applications, 2015. **22**(4): p. 789-796.

[15] Majcen, D., *Predicting energy consumption and savings in the housing stock - A performance gap analysis in the Netherlands*, in *Architecture and the Built Environment*. 2016, Delft University of Technology: Delft. p. 224.

[16] Filippidou, F., *Energy performance progress of the Dutch non-profit housing stock: a longitudinal assessment.* A+BE | Architecture and the Built Environment, 2018: p. 1-256%N 14.]

[17] Eurostat, *Energy consumption in households by type of end-use*, 2017 https://ec.europa.eu/eurostat/statistics-explained/index.php/Energy_consumption_in_households#Energy_consumption_in_households_by_type_of_end-use

Curriculum Vitae

Paula van den Brom was born in Eindhoven (the Netherlands) on May 16, 1988. In 2006 she started her Bachelor of Architecture at Delft University of Technology, where she graduated in 2009. Directly after the bachelor she started her Master degree at the same faculty. After studying a semester abroad in Berlin and doing an internship at an architecture office, she obtained her Master's degree Building Technology in 2013. One year later she graduated for a second time gaining her Architecture degree and was officially registered as an Architect in the Netherlands, which she still practices in her spare time. After her studies, Paula started working as a MEP consultant at "De Blaay van den Boogaard" in Rotterdam. In 2015 she returned to Delft University of Technology to start her PhD at the OTB department, while also taking part in the European TRIME project. She participated in several national and international research projects, published in several journals and taught multiple courses at Bachelor, Master and PhD level.

Publications

Journal papers

P. van den Brom., L. Itard, H. Visscher. (2020). *Calibration of building energy simulation models on a building stock level using actual energy consumption data – making building energy simulations a more reliable tool for policymakers.* submitted

P. van den Brom., A.R. Hansen, K. Gram-Hanssen, A. Meijer, H. Visscher. (2019). *Variances in residential heating consumption – importance of building characteristics and occupant behaviour analysed by movers and stayers.* Applied Energy

P. van den Brom., A. Meijer, and H. Visscher. (2019). *Actual energy saving effects of thermal renovations in dwellings—longitudinal data analysis including building and occupant characteristics.* Energy and Buildings. 182: p. 251-263.

P. van den Brom., A. Meijer, and H. Visscher (2017). *Performance gaps in energy consumption: household groups and building characteristics.* Building Research & Information, p. 1-17.

Conferences

P. van den Brom, A. Meijer, H. Visscher. (2019) *Parameters that influence the probability on lower-than-expected energy savings – a pre- and post-energy consumption analysis of 90,000 houses in the Netherlands.* CLIMA2019. Bucharest Romania

S. Ebrahimigharehbahi, F. Filippidou, P. van den Brom, Q. Qian, H. Visscher. (2019) *Analysing the energy efficiency renovation rates in the Dutch residential sector.* 2019 CLIMA2019. Bucharest Romania

P. van den Brom, A. Meijer, and H. Visscher (2017) *Dynamic versus Steady state building simulation – Preliminary analysis of an energy performance gap.* Energy in Buildings 2017 ASHRAE Helenic Chapter, Athens.

H., Visscher, F. Fillipidou, and P. van den Brom (2017) *Developments and challenges towards a carbon neutral housing stock in the Netherlands*. 2017 Proceedings of the International Conference on Advances on Sustainable Cities and Buildings Development (SB-LAB 2017). Amoeda, R. & Pinheiro, C. (eds.). Green Lines Institute for Sustainable Development, 9 p.

P. van den Brom, A. Meijer, and H. Visscher (2016) *Reducing the performance gap by analysing specific combinations of occupant and building characteristics*, BEHAVE 2016 4th European Conference on Behaviour and Energy Efficiency, Co

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Energy in Dwellings

A comparison between Theory and Practice

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Energy simulation models for buildings are widely used by policymakers, researchers and consultants as a tool to advice on the reduction of residential energy consumption. Previous studies have shown that there is a gap between theoretical building energy simulation results and actual energy use. The discrepancy between theory and practice is problematic, as for instance expected energy savings are often not achieved. This thesis shows that analysing *specific household types* and building characteristics can contribute to a better understanding of amongst others the influence of the occupant on actual energy consumption. The effectiveness of *thermal renovations* is dependent on both occupants and building characteristics, which means tailored advice on renovation measures is necessary. We also found that occupants and building characteristics are *equally responsible* for variances in actual residential energy consumption. To reduce the gap between theory and practice on a single building level, simulation models are improved using calibration methods. In the final part of this thesis, a method is developed to *calibrate simulations on a building stock level*, making building energy simulation tools more reliable for policymakers.

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