Exploration in-situ et numérique de la consommation énergétique et du confort thermique des bâtiments résidentiels en bois

Thèse

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RÉSUMÉ

Plus du tiers de l'énergie consommée et des émissions de gaz à effet de serre dans l'atmosphère sont causées par le secteur du bâtiment. Ce dernier joue ainsi un grand rôle dans la lutte au réchauffement climatique et il est impératif d'améliorer son efficacité énergétique, ce qui demande une excellente compréhension du comportement thermique des bâtiments. Les outils de simulation énergétique de bâtiments sont fort utiles à cet effet, mais il y a malheureusement souvent des écarts observés entre la consommation réelle d'un bâtiment et ce qui était attendu. Étant un aspect fort probabiliste de l'opération d'un bâtiment, le comportement des occupants est difficile à représenter fidèlement lors des simulations de bâtiments. Or, vu le grand impact que les occupants ont sur la performance d'un bâtiment, il est essentiel d'avoir une représentation viable de cet aspect de la simulation. L'objectif de cette thèse est d'analyser les dessous de la consommation énergétique des bâtiments résidentiels en bois à haute performance énergétique en se concentrant principalement sur le rôle joué par les occupants. Cette thèse se base sur le suivi détaillé d'un bâtiment de logements sociaux présentement en opération. Des pistes de solutions sont proposées dans le but d'améliorer davantage la performance des bâtiments à faible consommation énergétique.

Dans un premier temps, la consommation énergétique du bâtiment étudié est analysée de fonds en comble afin de comprendre pourquoi le bâtiment a besoin d'énergie. Cette évaluation expose de grandes variations de consommation énergétique et de confort thermique entre les logements. Cette grande variabilité n'est pas explicable ni par les différentes orientations et position des logements, ni par le nombre d'occupants dans les logements; les données montrent le grand effet que les gens peuvent avoir sur la performance de leur logement par les gestes qu'ils posent. Des modèles de régression linéaire sont formés à partir des données mesurées et quantifient l'impact de différentes variables sur la demande en chauffage en hiver et sur la température intérieure des logements en été. La température intérieure du bâtiment est un enjeu important puisque de la surchauffe est présente durant la saison estivale. La forte isolation et la grande étanchéité de l'enveloppe du bâtiment contribue à cette surchauffe en empêchant les transferts thermiques entre les environnements intérieur et extérieur. L'écart de performance énergétique du bâtiment étudié est également abordé. Il

est montré que pour cette étude de cas, l’écart est principalement par une mauvaise représentation du comportement des occupants dans le modèle numérique du bâtiment.

Un modèle stochastique simulant le comportement des occupants dans les bâtiments résidentiels est développé à partir de modèles déjà existant. Cet outil simule à la fois la présence des occupants dans leur logement, leur consommation d’eau chaude et d’électricité, ainsi que leur comportement vis-à-vis le contrôle des fenêtres. Les profils générés sont cohérents entre eux (il ne peut pas y avoir de consommation d’eau chaude si personne n’est présent) et considèrent la diversité inter-ménage du comportement des occupants. La portion traitant du contrôle des fenêtres est construite à partir des données mesurées au bâtiment étudié alors que ces données ont plutôt servies à guise de validation pour les autres parties du modèle. Cette validation montre les bienfaits des modifications apportés aux modèles déjà existants.

Des simulations sont par la suite effectuées pour quantifier l’impact des occupants sur la performance énergétique des bâtiments résidentiels. Ces simulations se basent sur l’outil stochastique du comportement des occupants développé durant cette thèse. Les résultats montrent que la demande en chauffage d’un logement, sa consommation totale d’énergie et son confort thermique sont très sensible aux gestes posés par les occupants. Un modèle de régression linéaire est également construit à partir des résultats de simulation pour mesurer l’influence des divers paramètres. Un bâtiment à plusieurs unités logements est moins robuste au comportement des occupants qu’une maison unifamiliale, mais les résultats suggèrent qu’il demeure difficile de prévoir avec exactitude la performance d’un bâtiment multirésidentiel si l’aspect stochastique du comportement des occupants est négligée. L’utilisation de profils plus précis du comportement des occupants peut aussi améliorer le dimensionnement des systèmes mécaniques, notamment les systèmes d’eau chaude.

ABSTRACT

Over a third of energy use and greenhouse gas emissions are related to the building sector. As part of global efforts to combat climate change, it is essential to ensure high energy efficiency of buildings. Doing so requires a deep understanding of the thermal behavior of buildings. Building performance simulation is very useful in this regard, but it is frequent to observe discrepancies between the predicted and real energy consumption levels. Occupant behavior is very influential on the energy performance of a building, so it is essential for it to be accurately represented during building simulations. The objective of this thesis is to analyze and explain the consumption of energy in high-performance wood residential buildings by focusing on the importance of occupant behavior. This thesis relies on the monitoring of a social housing building. Potential solutions are proposed to further improve the performance of low energy consumption buildings.

First, the energy consumption of the monitored building is studied in order to understand why the building requires energy. This analysis exhibits the great dwelling-to-dwelling variability of energy consumption and thermal comfort. This variability is not explainable by the various orientations and positions of the dwellings or by the different household sizes. This shows the great impact that actions taken by people at home can have on the performance of their dwelling. Linear regression models are created from the collected data to quantify the influence of multiple variables on the heating demand in winter and on the indoor temperature in summer. Indoor temperature represents an important issue since overheating is present in the building during the summer. The high insulation and air tightness of the building envelope contributes to overheating by preventing heat transfer between the indoor and outdoor environments. The energy performance gap of the building is also covered. It is demonstrated that for the case study building, the gap is mainly due to an inaccurate representation of occupant behavior during building simulations.

A stochastic model that simulates occupant behavior in residential buildings is developed from already existing models. This tool simultaneously simulates occupancy, hot water and electricity consumption and window control behavior. Generated profiles are coherent with each other (there cannot be hot water consumption when no one is present at home) and consider the dwelling-to-dwelling variability of occupant behavior. The window control part of the model is built from the data coming from the monitored building whereas the data is instead use to validate the other parts of the model. The validation shows the benefits of the modifications brought to the original occupant behavior models.

Building simulations are then performed to assess the impact of occupants on the energy consumption and thermal comfort of residential buildings. These simulations are based on the stochastic occupant behavior tool develop in this thesis. Results display that the heating demand of a dwelling, its total energy use and its thermal comfort are all highly sensitive to occupant behavior. A linear regression model is also built from simulated data to evaluate the influence of various parameters. The energy performance of large housing stocks is more robust with respect to occupant behavior, but the results suggest that it remains difficult to forecast with great accuracy the performance of a multiresidential building if stochastic aspects of occupant behavior are neglected. Use of more accurate occupant behavior profiles can also improve the sizing of HVAC systems, particularly of hot water systems.

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NOMENCLATURE

Variables

A	Surface area [m^2]
C_d	Discharge coefficient
c_p	Heat capacity [kJ/kgK]
cl	Clothing factor [clo]
CLT	Cross-laminated timber
CV	Coefficient of variation [%]
CV(RMSE)	Coefficient of variation of the root mean square error [%]
C_{vent}	Cooling rate introduced by ventilation
D	Total number of hours of operation [hours]
D_{avg}	Discomfort parameter of average temperature [°C]
D_{freq}	Discomfort parameter of frequency of overheating [hours]
D_{int}	Discomfort parameter of intensity of overheating [hours°C]
DHW	Domestic hot water
DW	Durbin-Watson statistic
ΔT	Difference of temperature [K,°C]
Δt	Duration of time [s, min]
E	Aggregated energy consumption [Wh]
f	Mechanical ventilation system use factor
g	Standard gravity [m/s^2]
h	Height above the neutral plane [m]
H	Window height [m]
HD	Heating demand [kWh/m^2]
I_{cons}	Overall consumption indicator [%]
$I_{dwellings}$	Dwelling-to-dwelling variability indicator [%]
I_{sched}	Timings of events indicator [%]
IHG	Internal heat gains [W]
LF	Light-frame
m	Measured variable
M	Annual number of events (Chapitre 4)
M	Mass of water [kg, lb] (Chapitre 5)
$\dot{m}$	Mass flowrate [kg/s, lb/min]
N	Total number of time steps
n	Number of observations
NHD	Number of hours of discomfort [hours]
NMBE	Normalized mean bias error [%]
P	Probability
P_{off}	Standby power consumption [W]

P_{on}	Operating power consumption [W]
Q	Energy [Wh]
q	Heat consumption rate [W, BTU/h]
q_{stack}	Airflow induced by stack effect [m^3/h]
q_{wind}	Airflow induced by wind [m^3/h]
R	Coefficient of determination [-]
s	Scale factor (Chapitre 4)
s	Simulated variable (Chapitre 6)
T	Temperature [°C, °F]
TEU	Total energy use [kWh/m^2]
U	Velocity [m/s]
V	Volume [m^3, L, gal]
V_{wind}	Wind speed [m/s]
$\dot{V}$	Flow rate [m^3/s]
W	Window width [m]
x	Regressors/Independent variable
y	Dependent variable

Greek letters

ϕ	Angle of opened window [°]
ρ	Density [kg/m^3]
μ	Distribution average value
σ	Standard deviation
λ	Event length [min]
δ	Daily aggregated amount of time spent on an activity [hours] (Chapitre 4)
δ	Electricity to internal heat gains ratio [W_{IHG}/W_{elect}] (Chapitre 6)
α	Regression coefficient related to the dependant variable (Chapitre 3)
α	Hot water to internal heat gains ratio [W_{IHG}/W_{DHW}] (Chapitre 6)
ω	Logit regression coefficient
γ	Occupant to internal heat gains ratio [W_{IHG}/occupant]
β	Regression coefficient
ε	Regression error
ε	Regression model error

Subscripts

air	Indoor and Outdoor air
c	Cold
Const	Constant
clo	Closure of windows
DHW	Domestic hot water
ΔT	Difference of temperature

eff	Effective
elect	Electricity consumption
h	Hot
in	Inside temperature
loss	Storage tank loss
op	Opening of windows
out	Outside temperature
peak	Consumption peak
q	Water heater
rad	Solar radiation
tank	Storage tank
vent	Mechanical ventilation
Wd	Wind direction
Ws	Wind speed
#Occ	Number of occupants

Superscript

-	Mean value
*	Standardized variable

REMERCIEMENTS

J'aimerais tout d'abord dédier cette thèse à ma tante, marraine et amie Sylvie. Malheureusement, Sylvie nous a quittés quelques mois avant la diffusion de ce document. Le courage et la détermination dont elle a fait preuve durant son combat auront été pour moins de puissantes sources de motivation pour l'achèvement de cette thèse. Je sais que Sylvie serait très fière de cette thèse. Je tiens à dire à Serge que nous serons toujours présents pour lui.

Dans un autre ordre d'idée, cette thèse est le fruit de la collaboration de nombreuses parties prenantes dont je me dois de mentionner. Tout d'abord, j'aimerais remercier mon directeur de recherche Louis Gosselin et mon codirecteur Pierre Blanchet. Les deux ont su me superviser durant mon projet afin de m'orienter vers les directions appropriées. Ils ont toujours été en mesure de trouver du temps pour moi malgré leurs horaires chargés. Je les remercie de n'avoir jamais hésité à m'ouvrir des portes et à me faire confiance. Sans eux, ce projet de recherche n'aurait jamais été possible.

Les travaux présentés dans cette thèse sont centrés autour d'un bâtiment multirésidentiel. La construction de ce bâtiment a été mandatée par la Société d'habitation du Québec (SHQ) et il est actuellement opéré par l'Office municipal du Québec (OMHQ). Ces deux organismes ont été des plus présents tout le long du projet et n'ont jamais hésité à répondre à mes questions ou à me fournir les informations demandées. Les entreprises Regulvar, BMD Architectes, Douglas Consultants, Génio Experts-Conseils, Genecor et Poly-Énergie ont également contribué à ce projet en m'offrant accès à leurs données ou leurs plans du bâtiment.

Ce projet a été financé par la chaire industrielle de recherche en construction écoresponsable en bois (CIRCERB) ainsi que par une bourse thématique en énergie octroyée par le Fonds de recherche du Québec – Nature et technologies (FRQNT). L'American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) m'a également financé en me remettant un *Graduate Student Grant-In Aid Award*. Le programme des Bourses canadiennes du jubilé de diamant de la reine Elizabeth II (BRE) et le Bureau international de l'Université Laval (BI) m'ont aussi donné des bourses qui m'ont permis d'effectuer un stage de recherche

à l'Université de Bath durant l'été 2016. Cette expérience fût des plus enrichissantes, autant d'un point de vue professionnel que personnel. Je tiens à souligner l'apport d'Alfonso Ramallo-González et Sukumar Natarajan qui m'ont supervisé durant ce stage et m'ont donné d'importants conseils qui ont grandement influencé cette thèse.

Je remercie tous les membres du Laboratoire de Transferts Thermiques et d'Énergétique (LaTTE) et du CIRCERB. Les deux groupes sont composés de gens passionnés et ont su construire une ambiance de travail des plus stimulantes et inspirantes. J'aimerais particulièrement mentionner les contributions respectives de Simon et Dominic dans l'avancement de mon projet doctoral. Chez le CIRCERB, j'aimerais souligner la contribution de Natalie Noël, qui s'est retroussé les manches à de nombreuses reprises pendant plusieurs mois en amont à mon arrivée dans le projet pour s'assurer de ce bon lancement. Le technicien Jean Ouellet fut également essentiel au projet par tous les problèmes qu'il a résolu en lien à l'instrumentation du bâtiment étudié. Durant les trois dernières années, Jean et moi avons dû faire des dizaines d'aller-retour au bâtiment pour régler des problèmes avec le système d'acquisition de données. Encore aujourd'hui, Jean craint chacun de mes appels car il présume alors qu'un nouveau problème est apparu.

Enfin, j'aimerais remercier les membres de ma famille rapprochée, soient Ginette, Marie-Josée et Yves. C'est grâce à eux que j'ai pu atteindre le niveau du doctorat. Vous êtes des modèles pour moi et m'avez appris à persévérer, à respecter ses prochains et à demeurer honnête et intègre.

AVANT-PROPOS

Les divers sujets abordés par cette thèse sont mis en contexte dans le Chapitre 1, qui présente également les objectifs auxquels les travaux de recherche tentent de répondre. Trois publications pour des journaux scientifiques (Chapitres 2, 4 et 5) ainsi que trois articles de conférence (Chapitres 3, 6 et Annexe A1) forment le corps de la thèse. L'article formant l'annexe A1 a été placé en annexe étant donné qu'une importante proportion de sa méthodologie et de ses conclusions sont reprises par l'article situé au sein du Chapitre 4. Les articles présentés dans cette thèse sont listés ci-dessous, avec des informations concernant mes contributions pour chacun d'entre eux ainsi que leur statut de publication.

Chapitre 1 :

J. Rouleau, L. Gosselin and P. Blanchet, "Understanding energy consumption in high-performance social housing buildings: A case study from Canada," *Energy*, vol. 145, pp. 677–690, Décembre 2017 (publié).

Notes: Article rédigé par J. Rouleau (moi-même) et révisé par L. Gosselin et P. Blanchet. J'ai effectué le rassemblement des données mesurées utilisées dans cet article en plus de leur analyse. Les modèles de régression linéaire présentés dans l'article ont été développés par moi-même sur Matlab. J'ai aussi effectué l'étude de l'écart de performance énergétique du bâtiment à partir du modèle numérique du bâtiment utilisé durant sa conception. J'ai également dégagé les principales conclusions. Le travail a été réalisé sous la supervision de L. Gosselin et P. Blanchet.

Chapitre 2 :

J. Rouleau and L. Gosselin, "Assessing the risk of overheating in high-performance social housing buildings with the use of regression analysis," *ASHRAE Annual Conference*, Houston TX, Juin 2018 (publié).

Notes: Article rédigé par J. Rouleau (moi-même) et révisé par L. Gosselin J'ai effectué le rassemblement des données mesurées utilisées dans cet article en plus de leur analyse. Les modèles de régression linéaire présentés dans l'article ont été développés par moi-même sur Matlab. J'ai également dégagé les principales conclusions. Le travail a été réalisé sous la supervision de L. Gosselin.

Chapitre 3 :

J. Rouleau, A. Ramallo-González, L. Gosselin, P. Blanchet, and S. Natarajan, "Adapting stochastic occupant behavior models into a unified tool for multi-residential buildings in Canada" *Energy Build.*, Mai 2018 (soumis).

Notes: Article rédigé par J. Rouleau (moi-même) et révisé par l'ensemble des co-auteurs, mais particulièrement par M. L. Gosselin. Cet article se base sur des modèles déjà existants dans la littérature. A. Ramallo-González m'a guidé vers ces modèles. Il rassemble ces modèles en un programme unique qui s'assure de les ajuster pour considérer les différences culturelles entre les pays où ces modèles ont été créés. Des facteurs considérant les différents types d'occupant sont également ajoutés. Tout ce travail de réassemblage et d'ajustements a été effectué par moi-même et a résulté en fonctions sur Matlab que j'ai écrit. J'ai aussi fait la validation des fonctions Matlab écrites. J'ai également dégagé les principales conclusions. Cette publication a été rédigée à partir de travaux effectués lors d'un stage à l'Université de Bath au Royaume-Uni. Le travail a ainsi été réalisé sous la supervision successive de A. Ramallo-Gonzalez et L. Gosselin.

Chapitre 4 :

J. Rouleau, L. Gosselin, and A. Ramallo-González, "Sizing methodology for domestic hot water systems based on simulated occupant behavior", *ASHRAE Annual Conference,* Long Beach CA, Juin 2017 (publié)

Notes: Article rédigé par J. Rouleau (moi-même) et révisé par A. Ramallo-González et L. Gosselin. Le concept de dimensionnement des systèmes à eau chaude a été conjointement pensé par L. Gosselin et moi-même. J'ai implémenté ce concept sur Matlab et Excel afin d'obtenir les résultats présentés dans ce texte. L'article se réfère à l'outil de simulation de la demande en eau chaude d'un bâtiment résidentiel que j'ai développé dans le cadre de l'Annexe A1. J'ai également dégagé les principales conclusions. Le travail a été réalisé sous la supervision de L. Gosselin.

Chapitre 5 :

J. Rouleau, L. Gosselin, and P. Blanchet, “Robustness of energy consumption and comfort in high-performance residential building with respect to occupant behavior” *Energy*, Août 2018 (soumis).

Notes: Article rédigé par J. Rouleau (moi-même) et révisé par L. Gosselin et P. Blanchet. J’ai créé les modèles de bâtiments dans TRNSYS en plus des codes MATLAB nécessaires pour utiliser en boucle les modèles TRNSYS. Les modèles de bâtiments utilisent l’outil de simulation des occupants que j’ai développé dans le cadre du Chapitre 4. À cet outil se rajoute un modèle d’ouvertures de fenêtre qui a été par moi-même. Je me suis occupé de la calibration et validation des modèles TRNSYS ainsi que de l’analyse des résultats de simulation. J’ai également dégagé les principales conclusions. Le travail a été réalisé sous la supervision de L. Gosselin et P. Blanchet.

Annexe A1 :

J. Rouleau, A. Ramallo-González, and L. Gosselin, “Towards a comprehensive tool to model occupant behavior for dwellings that combines domestic hot water use with active occupancy”, *ASHRAE Annual Conference*, Long Beach CA, Juin 2017 (publié)

Notes: Article rédigé par J. Rouleau (moi-même) et révisé par A. Ramallo-González et L. Gosselin. Cet article se base sur des modèles déjà existants dans la littérature, qui m’ont été fourni par A. Ramallo-González. Il rassemble ces modèles en un programme unique qui s’assure de les ajuster pour considérer les différences culturelles entre les pays où ces modèles ont été créés. Tout ce travail de réassemblage et d’ajustements a été effectué par moi-même et a résulté en fonctions sur Matlab que j’ai écrit. J’ai aussi fait la validation des fonctions Matlab écrites. La rédaction de cet article a été faite dans le cadre d’un stage à l’Université de Bath au Royaume-Uni. Le travail a ainsi été réalisé sous la supervision successive de A. Ramallo-Gonzalez et L. Gosselin.

Les seules modifications apportées aux articles insérés par rapport à leurs versions publiées ont été le changement de numérotation des équations, des tables et des figures. Aucun changement en lien au contenu n'a été apporté.

INTRODUCTION

Mise en contexte

Le citoyen moyen en Amérique du Nord passe plus de 90% de son temps au sein d'environnements intérieurs, que ce soit pour y vivre, y travailler, socialiser ou autres activités [1]. Les bâtiments sont attrayants puisqu'ils nous offrent un environnement confortable en nous protégeant des intempéries météorologiques et autres facteurs extérieurs. En hiver, nous apprécions la chaleur de nos maisons alors que durant les canicules en été, nous courrons les édifices ayant de l'air climatisé. Toutefois, ce confort offert par nos bâtiments ne tombe pas du ciel, car de l'énergie doit nécessairement être dépensée pour assurer le niveau de confort désiré. Cette énergie consommée a des retombées sur l'environnement, principalement par l'émission de gaz à effet de serre dans l'atmosphère.

C'est pour cette raison que le secteur du bâtiment représente un point névralgique de la lutte contre les changements climatiques. En effet, les bâtiments demandent 36% de l'énergie totale consommée sur la planète et cette consommation engendre 39% des émissions de gaz à effet de serre dans l'atmosphère [2]. La dépendance énergétique des bâtiments est un enjeu important et la réduction de cette dépendance demande aux professionnels œuvrant dans le domaine de se retrousser les manches. Ce constat explique les objectifs ambitieux d'efficacité énergétique que se sont fixés la plupart des organismes liés au domaine. Nous pouvons penser par exemple à l'ASHRAE qui souhaite être en mesure d'établir des bâtiments net zéro (bâtiments produisant autant d'énergie qu'ils en consomment) viables financièrement d'ici 2030 [3].

Pour améliorer l'efficacité énergétique des bâtiments, les bâtiments résidentiels sont particulièrement intéressants parce qu'ils forment la principale cause derrière les pointes journalières de consommation énergétique que les réseaux énergétiques subissent [4]–[6]. Chaque matin et chaque soir, la puissance énergétique consommée par une communauté augmente drastiquement puisque les gens sont à la maison et consomment par toutes sortes de manières plus d'énergie (douche, préparation des repas, télévision…). Parfois, il arrive que le fournisseur d'énergie ne soit pas en mesure de répondre par ses propres moyens à la demande des clients et qu'il importe donc de l'énergie provenant de sources plus dispendieuses et moins écologiques. Par exemple, dans le contexte québécois, lors des moments de grandes demandes en puissance se produisant au plus froid de l'hiver, il arrive à Hydro-Québec de devoir importer de l'électricité produite hors de son réseau. Cette électricité est habituellement produite à partir de combustibles fossiles non renouvelables et est fournie par l'exportateur à haut prix. L'amélioration de la performance énergétique des bâtiments résidentiels a ainsi un double effet puisqu'en plus de réduire la consommation globale d'énergie de la société, la gestion de ces pointes journalières de puissance consommée est facilitée.

Pour optimiser l'efficacité énergétique des bâtiments résidentiels, il faut posséder une bonne compréhension de la consommation énergétique de ces derniers. La simulation énergétique de bâtiments représente un puissant outil pour approfondir notre compréhension. L'emploi de logiciels de simulation (eQuest, TRNSYS, EnergyPlus, PHPP…) permet de projeter les besoins en énergie de plusieurs configurations d'un bâtiment donné selon divers scénarios. L'utilisateur peut ainsi choisir un design de bâtiment qui mènera à une faible demande en énergie. Cependant, il s'avère fréquent que la consommation réelle d'un bâtiment diverge de ce qui avait été prévu par un tel outil de simulation, un phénomène nommé « l'écart de performance énergétique » [7]–[9]. En effectuant une revue de la littérature, van Dronkelaar et al. ont trouvé que l'écart de performance énergétique moyen d'un ensemble de 62 bâtiments de tout genre était de +34% (sous-estimation de la consommation réelle) avec un écart-type de 55%, montrant l'amplitude de ce phénomène [10].

Cet écart entre la prédiction et la réalité s'explique par le fait que la simulation énergétique de bâtiments fait appel à de nombreuses hypothèses qui peuvent influencer le résultat de la simulation. Tronchin et Fabbri ont essayé de prédire la consommation d'une maison unifamiliale en Italie en employant trois méthodes de calculs distinctes. Ils ont noté que les trois méthodes menaient à un écart de performance significatif, mais aussi que les niveaux de consommation prévus variaient selon la méthode de calcul employé [11]. Jones en est venu à des conclusions semblables lorsqu'il a demandé à six étudiants gradués de créer leur propre modèle d'un édifice à appartements [12]. Les prédictions de consommation énergétiques de bâtiments résidentiels sont donc très sensibles à la méthode de calcul et aux hypothèses utilisées.

Ces hypothèses se rattachent non seulement aux variables physiques du bâtiment (enveloppe, systèmes mécaniques…) et aux conditions météorologiques, mais également au comportement des occupants [13]–[15]. Le comportement des occupants est défini comme étant l'ensemble des gestes posés par une personne qui peut avoir un effet sur la demande en énergie et le confort thermique d'un bâtiment. Puisque le comportement des gens au sein de leur logement varie jour après jour et qu'il est différent d'un logement à l'autre, il possède un caractère hautement probabiliste qui le rend très difficile à représenter dans le cadre de simulations énergétiques. C'est particulièrement le cas pour les bâtiments résidentiels puisque les occupants ont moins de contraintes pouvant limiter leurs actions au sein de leur logement.

Or, le comportement des occupants peut fortement affecter la consommation d'un bâtiment [16]. En effectuant une analyse de sensibilité des paramètres affectant le plus la demande de chauffage d'un bâtiment résidentiel au Pays-Bas, Ioannou et Itard ont remarqué que les incertitudes sur les variables reliées aux occupants avaient beaucoup plus d'importances que celles des variables reliées aux systèmes du bâtiment [17]. Dans l'ensemble, il a été démontré que des habitudes d'opération de bâtiment non énergétiquement efficaces pouvaient augmenter la demande en chauffage d'un bâtiment par un facteur d'au moins deux [18]. De plus, avec l'amélioration constante de la qualité des bâtiments, l'impact des occupants devient de plus en plus important dans le bilan énergétique d'un bâtiment [19]. Il devient essentiel de bien représenter les occupants lors des simulations énergétiques de bâtiments pour améliorer leurs prédictions par rapport à la performance du bâtiment étudié.

C'est donc autour de sujets tels que la performance énergétique des bâtiments résidentiels, les simulations et leurs écarts de performance énergétique et le rôle joué par les occupants que cette thèse est articulée. La thèse se concentre sur les bâtiments ayant une structure de bois. Puisqu'il s'agit d'un matériau à faible impact environnemental, le bois se présente comme étant un matériau de l'avenir pour le domaine de la construction; pour cette raison, il est important de saisir comment des bâtiments basés sur ce matériau se comportent d'un point de vue énergétique. La thèse se base ainsi sur l'instrumentation et le suivi d'un bâtiment en bois de logements sociaux, qui porte le nom de *Les Habitations Trentino*. Situé dans la ville de Québec, ce bâtiment est un outil de démonstration mis en place par la Société d'Habitation du Québec (SHQ) pour montrer la faisabilité et la rentabilité des bâtiments à faible consommation énergétique. Différentes mesures ont ainsi été implantées pour diminuer les besoins en chauffage du bâtiment; ces mesures seront décrites au fil des chapitres de cette thèse. *Les Habitations Trentino* ont aussi la particularité d'être composées de deux structures distinctes de bois. L'analyse des données provenant de ce bâtiment réellement opéré sont au centre de cette thèse et apportent à la communauté de l'information inaccessible par les méthodes conventionnelles de la simulation énergétique.

Objectifs

L'objectif principal de cette thèse est d'approfondir notre compréhension de la consommation énergétique et du confort thermique des bâtiments résidentiels en bois à haute performance énergétique. Le but est d'identifier des pistes de solutions favorisant l'amélioration de l'efficacité énergétique de tels types de bâtiments. Étant donné le grand rôle qu'ils ont à jouer, ces solutions se concentreront principalement sur les occupants et leur comportement à domicile. Pour ce faire, cette thèse est centrée autour des axes de recherche suivants :

1. Le suivi assidu de la performance énergétique d'un bâtiment multirésidentiel dans le but de comprendre concrètement son comportement énergétique.
2. L'élaboration d'un modèle stochastique de comportement des occupants dans des bâtiments résidentiels en rassemblant des outils disponibles dans la littérature.
3. L'étude de l'influence des occupants sur la performance d'un bâtiment résidentiel en bois en considérant la diversité inter-ménage du comportement des occupants lors de la phase de conception du bâtiment.

Des objectifs spécifiques sont reliés à chacun de ces trois axes, tel que décrit dans les sous-sections 1.2.1 à 1.2.3. Trois articles de journaux scientifiques et trois articles de conférence ont été rédigés dans le but de répondre à ces objectifs. Les sections 1.2.1 à 1.2.3 révèlent également à quels chapitres de la thèse chaque axe de recherche est associé.

Axe 1: Suivi de la performance d'un bâtiment multirésidentiel

Une évaluation post-occupationnelle d'un bâtiment est un exercice fort utile pour bien comprendre le comportement thermique d'un bâtiment. Par l'analyse de données, elle permet d'établir différentes corrélations permettant d'estimer les besoins en énergie et le confort thermique d'un bâtiment. Les Chapitres 2 et 3 se basent sur une telle évaluation afin de répondre aux objectifs spécifiques suivants :

1.1 Comprendre où l'énergie des bâtiments à haute performance est consommée et quels sont les principaux facteurs d'influence de cette consommation.

1.2 Étudier la présence potentielle d'un écart de performance énergétique et si écart il y a, l'expliquer.

1.3 Analyser la possibilité de construire des modèles statistiques permettant de prévoir la consommation d'énergie et le confort thermique d'un bâtiment.

1.4 Comparer avec des données in-situ la performance thermique d'un bâtiment avec une structure légère en bois versus celle d'un bâtiment utilisant une structure massive.

1.5 Évaluer le potentiel que la ventilation naturelle possède pour contrôler les températures intérieures estivales d'un bâtiment à haute performance énergétique.

Axe 2 : Élaboration d'un modèle stochastique des occupants

Étant donné leur grande importance, il est crucial de représenter fidèlement les occupants lors des simulations énergétiques des occupants. La littérature scientifique se concentre donc de plus en plus sur la création de modèles stochastiques du comportement des occupants pour mieux saisir son aspect probabiliste. Le Chapitre 4 (ainsi que l'Annexe A1) présente un outil centralisateur de modèles déjà existants qui a été développé dans le but de pouvoir simuler les différents types d'occupants. Cet outil a été construit pour atteindre ces objectifs :

2.1 Centraliser différents modèles touchant à un seul aspect du comportement des occupants en un outil unique.
2.2 Considérer la diversité de comportement inter-ménage lors de la simulation énergétique de bâtiments résidentiels.
2.3 Adapter des modèles de comportement conçus outremer au mode de vie canadien.
2.4 Évaluer l'effet des modifications apportées sur les profils d'occupant générés.

Axe 3 : Étude de l'influence des occupants sur les bâtiments résidentiels

Le troisième axe de recherche profite de l'outil développé lors du deuxième axe pour évaluer l'impact que les occupants ont sur la performance énergétique d'un bâtiment à haute performance énergétique. Cette évaluation est couverte par les Chapitres 5 et 6. À mesure qu'on améliore les systèmes des bâtiments pour les rendre de plus en plus efficaces, on se rend de plus en plus compte de la grande importance que les occupants ont. Cet axe de recherche s'intéresse à quantifier cette importance autant pour la performance d'un bâtiment résidentiel que pour le dimensionnement de ses systèmes. L'axe 3 tente spécifiquement de répondre aux tels objectifs :

3.1 Quantifier l'impact global des occupants sur la performance énergétique d'un bâtiment.
3.2 Isoler l'influence des différents aspects du comportement des occupants (température de consigne, consommation d'eau chaude…).
3.3 Évaluer l'intérêt de considérer l'aspect stochastique du comportement des occupants lors des simulations de bâtiment.
3.4 Comprendre comment la représentation des occupants lors de la phase de conception d'un bâtiment peut affecter le dimensionnement de ses systèmes.

CHAPITRE 1. UNDERSTANDING ENERGY CONSUMPTION IN HIGH-PERFORMANCE SOCIAL HOUSING BUILDING: A CASE STUDY FROM CANADA

Résumé

Cet article présente le suivi énergétique d'un bâtiment de logements sociaux à haute performance énergétique. Le but est de comparer les niveaux de consommation d'énergie prédits et réels ainsi que d'identifier les paramètres ayant le plus d'influence sur les besoins en énergie. Un système d'acquisition de données enregistre des mesures prises sur le bâtiment à une fréquence de 10 minutes. Le bâtiment étudié a la particularité d'être composé de deux sections symétriques utilisant des systèmes structuraux en bois distincts. Aucune différence notable de consommation d'énergie est détectée entre les deux parties du bâtiment. Toutefois, une grande variabilité est observée lorsqu'on compare la consommation individuelle de chacun des logements et ce, peu importante leur structure. L'impact de l'orientation du logement semble minimal par rapport à cette variabilité, ce qui suggère que le comportement des occupants est le facteur dominant qui explique la variabilité inter-ménage de consommation. Des analyses de régression linéaire montrent que certains aspects du bâtiment qui sont contrôlés par les occupants, comme l'ouverture de fenêtres en hiver ou l'utilisation d'appareils électriques, ont un grand impact sur le bilan énergétique des logements. En 2016, l'écart de performance énergétique entre la consommation prévue pour le bâtiment et celle mesurée était de 74%. Les données récoltées sur le bâtiment ont permis d'identifier les causes de ce grand écart.

Abstract

This paper presents a case study of a recently built high-performance Canadian social housing building with the aim of comparing the expected and measured energy consumptions and to identify the parameters affecting the most the energy need. A monitoring system compiles at a 10-minute frequency information related to the energy use and the thermal conditions observed in the building and its HVAC system. The building has the particularity of comprising two symmetric sections made of different timber structure systems. No significant differences of energy consumption were detected between the two parts of the buildings. However, a large variance was observed when comparing each dwelling individually regardless of their structures. The orientation of the dwelling also exhibited a minimal influence compared to these variations, suggesting that occupant behavior is the dominant factor explaining dwelling-to-dwelling variability and is thus critical for understanding energy use in residential buildings. Regression analysis showed that specific occupant actions, such as opening windows in winter or using electrical appliances, have a great impact on the energy balance of the apartments. In 2016, the performance gap between measured and expected total energy demand of the building was 74%. With the use of the large dataset coming from the building, it was possible to determine the causes behind this large gap for the reference building.

1.1 *Introduction*

Improving the energy performance of buildings represents a crucial component for achieving a more sustainable management of energy. 40% of the energy consumed in the US is used by buildings [20] and a similar proportion is observed in Europe [21]. Consequently, building-related stakeholders such as the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) or the European Performance of Buildings Directive (EPBD) have established ambitious objectives for the next 15 years. For example, the goal that ASHRAE is attempting to establish is to produce market-viable Net Zero Energy Buildings (NZEBs) by 2030 [22]. Similarly, the EPBD wants new buildings in 2020 to be close to this NZEB target [23].

A great understanding of building physics is necessary to accomplish these tasks since improving a design becomes more and more difficult as buildings get more efficient. Buildings are complex systems, the energy performance of which involves heat and mass transfer through the envelope, windows characteristics, ventilation strategy, solar radiation, internal gains, decision-making of the occupants, efficiency of the HVAC systems, and so on. Identifying the most effective ways to reduce energy consumption in buildings is thus not trivial. It is particularly the case for residential buildings due to the high diversity of occupant behaviors observed in such buildings, leading to large variations of energy demand even between very similar buildings [24]. Since people spend the majority of their time at home, residential buildings play an important part in the energy demand and are responsible for peak demands incurred by energy providers. As a result, residential buildings have a distinct contribution within the building sector.

In-situ evaluation of building energy performance is helpful for increasing our knowledge on building physics and are critical for energy saving analyses. Data obtained during the assessment of a building performance has been used to accurately depict energy consumption for supermarkets [25], residential [26]–[28], commercial [29], [30] and office [31] buildings. For example, Kneifel and Webb were able to build a regression model for NZEBs that provide a viable baseline for evaluating energy consumption comparable to a traditional simulation model, but with far lower computational efforts [32]. Such models allow the direct quantification of the impact of various parameters (indoor and outdoor temperatures, solar radiation…) on the energy consumption of a building. For residential buildings, Catalina et al. proved with a regression analysis that the shape of the building and its thermal inertia have a significant impact on its energy demand [26]. Measured data can even be used in regression analysis to quantify impacts of social factors on energy consumption as revealed by Chen et al. who found that resident age has a larger influence than their income [33].

Another reason to record data from real buildings is related to a major weakness of currently used numerical models – their lack of accuracy. An important energy performance gap (EPG) is typically seen between the actual energy consumption of a building and the one predicted by numerical simulations [34]–[37]. In a study covering more than 950 homes, Tronchin and Frabbi estimated the energy demand of a house using different methodologies which all yielded energy performance gaps, demonstrating that the gap is present regardless of the computational method [38]. Jones obtained a similar conclusion when he asked six graduate students to create their own model for an apartment building without consulting each other [39]. The six models had completely different predictions for the building annual energy consumption (ranging from 2,654 to 4,292 kWh) that were all far from the true demand (2,170 kWh). The energy performance gap is thus not only caused by the computational method or simulation software, but also by the modelers themselves. Building simulations require a vast quantity of input parameters that usually need to be approximated. Inadequate decisions on these parameters and poor awareness of their impacts of the simulations results lead to predictions that are off [40]. Measured data can be used to calibrate models in order to circumvent this lack of accuracy. The lack of available data for model calibration can be a problem for building simulations [41]. Without validation, numerical models cannot be employed to their full potential.

Studies in the past have relied on numerical methods based on energy modeling to quantify drivers of energy use in buildings, usually by adopting a bottom-up approach [42]–[45]. Liu *et al.* for instance used sensitivity analysis to assess the importance of meteorological parameters in building energy consumption [46]. They found that temperature had the strongest effect on both heating and air conditioning energy use and that global solar radiation did not directly affect building energy demand. Except for the relative humidity, the weather variables were more important for heating in winter than for air conditioning in summer. A similar procedure was applied on the occupant actions in a Passivhaus dwelling which revealed that the set point temperature, the use of electrical appliances and the ventilation behavior all influence heating demand [47]. An artificial neural network trained with building models supports the findings of the previous study in that it estimated that in an airtight and well-insulated building, reducing the set point from 22 to 20°C could decrease by approximately 35% the need of heating [48]. Occupancy of a residential building is another important parameter as there is a direct link between energy consumption of a dwelling and the occupancy patterns of its household [49]. These studies demonstrate the impact of occupant behavior and of weather on the energy demand of a residential building, but they are based on numerical building models that are not always fully validated. It would be beneficial to research similar aspects by employing a top-down approach that is entirely based on measurements coming from real buildings.

Although literature contains a vast amount of studies in which residential buildings were experimentally evaluated, a limited number of assessments of multi-residential buildings is found. Although the energy performance gap was generally observed in these studies. Since occupants are difficult to model in multi-residential buildings due to the high number of households, occupant behavior is usually suspected to be the main culprit behind the energy performance gap that is generally observed in these studies. Nonetheless, to the knowledge of the authors, no thorough analysis has been made in apartment buildings to confirm the sources of the energy performance gap. For instance, Calì examined the discrepancy between expected and observed energy consumption of three apartment buildings following refurbishment during four successive years [50]. The relative difference between expectations and observations during these years varied from 41% to 117%. These differences were explained by technical issues (distribution losses of the DHW system in this case) and occupant behavior. Calì then used data recorded during his study to quantify the impact of the set point temperature and of the average window position on the heating energy consumption. It was found that while the former has a moderate impact, the latter surprisingly has no tangible impact on a dwelling's consumption. However, when evaluating the energy performance gap, Calì was unable to separate the role of the occupants and that of the technical issues and thus could not quantify the impact of occupant behavior on the EPG. In another study, the impact of occupant behavior was also easily observable in an apartment building in Italy [51], [52]. In the sample of 196 apartments contained in this building, the heat consumption of each dwelling during a winter season ranged from 0.0 to 62.4 kWh/m^2 in spite of high similarity of the dwellings. Similar variation was seen for domestic hot water (DHW) consumption (50 to 350 L/day per dwelling) and summer cooling demand (0 to 56 kWh/m^2). Preliminary analyses made by the authors suggested that the number of occupants and the heating and cooling set point temperatures, all variables that depend on occupancy, could be behind these differences, but in-depth study was made to confirm the significance of these parameters.

The present paper analyzes the energy demand of a high-performance social housing building that has been thoroughly monitored in real-time since 2015. Various aspects, such as window openings, indoor temperatures and DHW consumption, are measured in addition to the heating energy demand of each apartment. The building is described in Section 2, along with the energy modeling done during the design phase and the monitoring system that has been installed. Section 3 presents different thermal patterns found during the evaluation of the building energy performance. This is followed in Section 4 by a regression analysis that is done to assess which parameters drive the heat consumption in winter. Finally, the paper ends with a study on the energy performance gap where the pre-construction model of the building is explained using post-occupancy data. In this manner, the influence of each erroneous hypotheses could be quantified. In short, the aim of this paper is to use a case study building to increase our understanding of multiresidential buildings physics in order to help reduce energy performance gaps in the future.

1.2 *Monitoring of the case study building*

1.2.1.1 <u>Case study building</u>

The monitored building is a recently built multiresidential social housing building located in Quebec City, Canada. Most of the 40 dwellings located in the building are inhabited by young families – the population's mean age is 26.6 years old. For the sake of comparison, the average age of the population of Quebec City in 2016 was 43.2 years old [53]. A total of 90 people (2.25 per residential unit) live in the building. It was built with the objective of serving as a demonstration of the practicability and profitability of high-performance social residential buildings in the Province of Quebec. Its design drew heavily on the Passivhaus approach: it has a compact shape (surface-to-volume ratio of 0.28 and form heat loss factor of 1.14) and a highly insulated envelope (U-values of 0.157 W/m^{2}K for vertical walls and 1.15 W/m^{2}K for windows) to reduce heat losses, a continued insulation to minimize thermal bridges and a high airtightness (0.6 air change per hour at 50 Pa) to limit infiltrations. In addition to heat-recovery ventilator units recovering up to 85% of the exhaust air thermal energy, solar walls were installed to preheat outdoor air during the heating season. The ventilation system has a total capacity of 4,000 m^3/h. It is a 100% fresh air system in which the primary air is only tempered, i.e. most of the heating is provided by radiators in each dwelling. Note that the occupants in each dwelling have access to their own on/off switch for the ventilation system. A district heating hot water loop provides the required heat for the building, via heat exchangers. The thermal energy of the district system is transferred to all dwellings for space heating by ventilation and radiators. Domestic hot water is also obtained by using heat from district heating. Occupants do not receive separate bills for thermal energy as it is already included in their lease (electricity however is not included in the lease, so each household has its own electricity meter). In summer, there is no mechanical system to cool the air – overheating is controlled solely by natural ventilation. The reference building is presented in more detail in Table 1.1, which summarizes the characteristics of the case study building, and Fig. 1.1, which offers a visual depiction. In the floor plan, dwellings in green have light-frame wall assemblies whereas yellow dwellings use a CLT structure.

Table 1.1. Characteristics of the building envelope and HVAC system chosen during the design phase.

Type of structures	CLT	LF
Treated floor area [m^2]	3024.50	
Exterior wall area above grade [m^2]	1672.9	
Exterior wall area below grade [m^2]	114.58	
Roof area [m^2]	773.20	
U_e (Exterior walls) [W/m^2K]	0.158	0.157
U_r (Roof) [W/m^2K]	0.138	0.107
U_s (Floor slab) [W/m^2K]	0.539	
U_b (Basement walls)	0.301	
Fenestration type	Triple glazing, low-E, Argon	
U_g (Glazing) [W/m^2K]	0.790	
U_f (Window frame) [W/m^2K]	1.330	
Window-to-wall ratio	16.0%	
g-value	0.56	
Ventilation average air change rate [1/h]	0.41	
Ventilation heat recovery efficiency	85%	
Ventilation electric efficiency [kJ/m^3]	3.1	
Air change rate at pressure test [1/h]	0.60	

Figure 1.1. a) Northeast façade of the building and b) Floor plan of the building.

One side of the building employs light-frame wall assemblies (LF) for the structural system, whereas the other side relies on massive timber panels (cross-laminated timber (CLT)). This particular use of two constructive systems in the same building was specifically chosen to compare their energy performance and the easiness and cost of their implementation. Quebec's construction traditionally uses wooden light-frame for residential buildings. It has the advantage of being an economical structure in terms of capital and materials. However, light-frame wall assemblies cannot be used for buildings over six stories, hence the appeal of CLT, an engineered building system with superior structural properties than light-frame structures. A barrier for the growth of CLT in North

America is the lack of familiarity with this product. A survey has shown that building professionals felt more confident of the viability of CLT in high-rise construction once they knew the capabilities of the product [54]. Both sides of the building are symmetrical sections that are separated by a common wall. The thermal resistance of the vertical walls is approximately the same in both sections. The case study building can thus serve as a direct comparison between the thermal performances of an envelope based on a CLT structure and that of a light-frame wall assembly. However, the U-values for the roofs are different in the two sections of the building (0.138 W/m^2K for CLT versus 0.107 W/m^2K for LF). Furthermore, the CLT section is more oriented towards the south whereas the LF section is in the north direction, which could also induce variations of energy performance.

1.2.2 Predictions of energy demand during the design phase

Prior to its construction, the building was modelled on the Passivhaus software *Passive House Planning Package* (PHPP) [55]. PHPP is a static model developed by the Passivhaus Institute (PHI) to help building professionals in designing low-consumption buildings and its use is mandatory to receive a Passivhaus certification. Therefore, its use is increasing all around the world [56]. As it uses a monthly method to calculate heat demand, users of PHPP must prescribe a monthly weather profile along with the total population of the building and the type of building (residential or non-residential). An indoor air temperature of 20°C is assumed by the software as the Passivhaus Institute requirements ask for energy calculations to be based on this temperature. With these inputs, the main estimations provided by the PHPP relevant to the present paper are:

- Specific annual space heat demand (kWh/m^2a);
- Specific space heating load (W/m^2);
- Specific total energy demand (kWh/m^2a);

For the simulation of the case study building, an expected population of 112 occupants (27 m^2/person) was used. This is 24% higher than the current observed population. With these inputs, the software projects that the building would require 16.6 kWh/m^2a for space heating (radiators and ventilation) with a heating peak load of 12.6 W/m^2, meaning that the building does not meet Passivhaus specifications (respectively, 15 kWh/m^2a and 10 W/m^2) as defined in [56]. The volume of fresh air entering the building by the mechanical ventilation system was set to 3,080 m^3/h, which is 77% of the system maximum capacity. Figure 1.2a summarizes in a Sankey diagram the energy balance forecasted by the software. Values on the diagram represent the energy intensity in $kWh/m^2a.$, with SG representing the solar gains and IHG the internal heat gains. The "waste heat" outlet represent the balance of energy consumed by electrical appliances and lighting and the useful heat generated by these devices. The internal heat gains from these appliances is usually equal to the amount of electricity that they demand, except for the fact that part of that heat is unused (e.g.: during the summer, when the kitchen hood is activated…). An annual total of 42.4 kWh/m^2 of heat is lost by the thermal envelope and ventilation system. 61% of the losses are compensated by useful solar and internal gains, reducing the energy demand of the space heating system to 16.6 kWh/m^2y to maintain a constant air temperature of 20°C. Excluding solar gains and heat generate by occupants, the total energy consumption is expected to be 74.3 kWh/m^2y. The major source of consumption are the DHW use (26%), the waste heat coming from electrical appliances (21%), windows (13%) and vertical walls (10%).

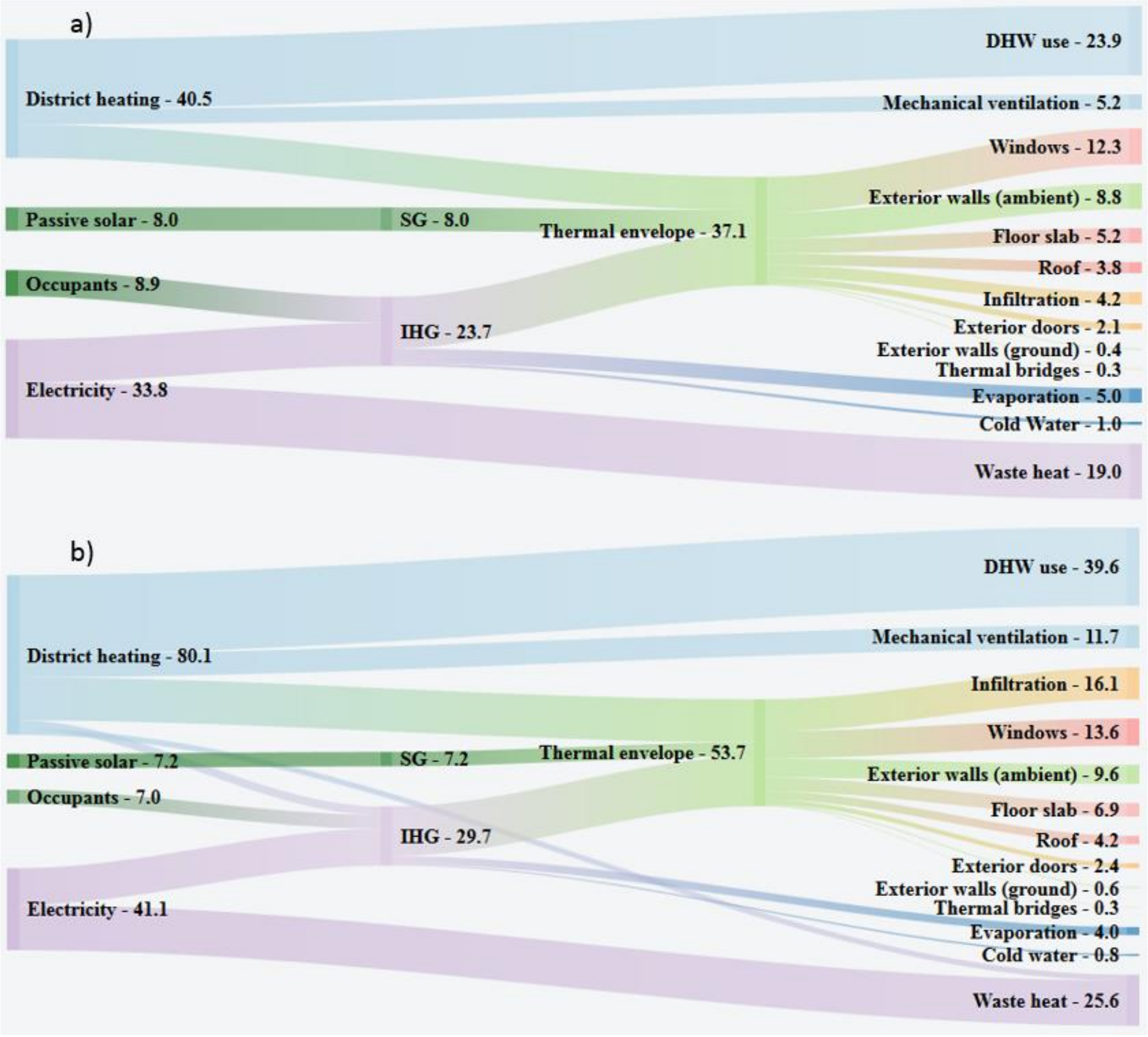


Figure 1.2. Energy balance of the reference building according to a) the initial version of the numerical model and b) the revised version in Section 2.5.

1.2.3 Monitoring system

A monitoring campaign that focuses on the characterization of the energy use in both sections of the building started on October 2015. During this period, approximately 350 measurement points were registered continuously, except from mid-July 2016 to the beginning of September 2016 (due to a problem with a data logger). Data presented in this paper covers the period from January 1st 2016 to January 1st 2017. Since energy data are recorded by the sensors in a cumulative way, it was possible to recover the total energy use during the period with missing data – it was the detailed time distribution of the consumption of this quantity of energy that was lost during that period. Year 2016 was warmer than usual (mean temperature ~1.5°C above the one of the standard weather profile). Sensors were used to probe water temperatures (with an accuracy of ±0.5%) , flow (±5%) and energy (±5%) in pipes throughout the building, enabling the measurement of heat energy use at multiple points [57]. These sensors were installed in the heat exchangers used to extract heat from the district heating network, in the radiators of all apartments and in the coils that provided energy to the ventilation system. With this configuration, it is possible to both quantify the total heat consumption of the building and to identify where exactly this energy is spent. The same sensors were installed in the domestic hot water loop to measure DHW demand for each of the dwellings and the total energy use for DHW. Electricity demand is registered each month with electricity meters.

Eight of the 40 apartments were specifically targeted for the installation of additional sensors. These eight "super-monitored" residential units are those situated on the eight corners of the building, i.e. four on the first floor vs four on the fourth floor; four on the northeast façade vs four on the southwest façade; four in the CLT section vs four in the LF section. Air temperature and relative humidity in all rooms of these dwellings measured by the control system were recorded, along with electricity consumption and the state of the mechanical ventilation system (on/off). The accuracy of the air temperature and humidity measurements respectively was ±0.2°C and ±3% [58]. In addition, sensors were installed in these apartments' windows to monitor their state (open/close).

Table 1.2 provides the overview of the data that is provided by the monitoring system. Data are logged every 10 minutes, except for the windows state which is measured at a 1-minute frequency. Weather data, measured every hour, are obtained from a weather station located within one kilometer of the building site. These include temperature (accuracy of ±0.1°C) [59], humidity (±0.8%) [60], wind velocity (±0.3 m/s or 1% of reading) and direction (±3°) [61], global radiation (±4%) [62] and precipitation (±0.05 mm) [63].

Table 1.2. Overview of the data recorded in the case study building.

	For the 8 "super-monitored" dwellings	For the 32 remaining dwellings	For the whole building
Air temperature [°C]	✓		
Relative humidity [%]	✓		
Ventilation system control [On/Off]	✓		
Windows opening control [On/Off]	✓		
Electricity consumption (10-min) [kWh]	✓		✓
Electricity consumption (1 month) [kWh]		✓	
Space heating [kWh]	✓	✓	✓
DHW [L]	✓	✓	
DHW [kWh]			✓
Heat energy for ventilation [kWh]			✓
Weather data			✓

1.3 *Evaluation of the building energy performance*

In this section, an analysis of the energy consumption of the building is made based on the monitoring data. During this evaluation, several notable observations were visible regarding the building's heat and hot water demand and the variability of energy consumption between every dwellings.

1.3.1 Building heat demand

In 2016, the building consumed a total of 111.6 MWh of energy for space heating (ventilation and radiators), translating into an energy intensity of 36.9 kWh/m^2. Based on heating degree-days, accounting for the fact that 2016 was warmer than the reference year would modify this consumption level to 38.7 kWh/m^2. Radiators located in dwellings used 63.7% of this energy (23.5 kWh/m^2) and the rest (13.1 kWh/m^2) went into the ventilation system (which only provides tempered air at around 20°C to the zones).

During the heating season, which is defined as going from January to April and then from October to December, the mean set point temperature found in the eight "super-monitored" apartments is 23.9°C. Considering the sample size and the total number of dwellings, applying this number as the building average set point temperature yields a margin of error of 1.0°C, 95% of the times. It was reported in 2011 that the average set point temperature in Canadian households is 20.8 °C [64]. These figures convey that the indoor temperature in the case study building during the heating season tends to be higher than the one found in average households. Tenants not having to pay directly for the dwelling's thermal energy consumption might explain to some extent the high set point temperature.

The LF section of the building required a total of 57.4 MWh of heating (38.8 MWh through the radiators and 18.6 via ventilation) versus 54.2 MWh for the CLT section (32.2 MWh for radiators and 22.0 by ventilation), meaning that no considerable difference of consumption is observed between both types of wall assemblies. It is hard to conclude on the superiority of the CLT envelope over the LF since the narrow gap can also be related to occupant behaviors or to the fact that the CLT section is in the south part of the building. Figure 1.3 presents in a scatter plot the heat load during the heating season for both sections of the building in relation to the difference between the outdoor and indoor temperatures (assumed to be equal to mean temperature observed in the "super-monitored" dwellings). Each dot represents the conditions observed every four hours (heat load and temperatures are averaged over this period of time). The LF and CLT sections have a nearly identical relationship with temperatures that is clearly linear. The possible effect of the larger thermal inertia in CLT wall assemblies on heat load is not clearly observed. The best fit curve yields the same equation for both sections of the building:

$$q = 0.45\Delta T_{air} - 4.86 \tag{2.1}$$

with a coefficient of determination of R^2=0.83 for the LF section and R^2=0.81 in the CLT building, showing a strong correlation between heating load and temperatures. The slope of the line (0.45 W/m^{2}K) provides the effective thermal conductance of the building, including heat losses through the envelope and the ventilation system. Eq. (2.1) suggests that no heat is needed when the difference of temperature is below 10.8°C (which corresponds to an outdoor temperature of 13.1°C). A base temperature of 18°C is traditionally used in the US to calculate heating degree-days [65]. A study made in South Korea showed that the base temperatures ranged from 14.7 to 19.4 °C according to the location and the specifications of the buildings [66]. A base temperature of 13.1°C thus demonstrates the high-efficiency of the reference building.

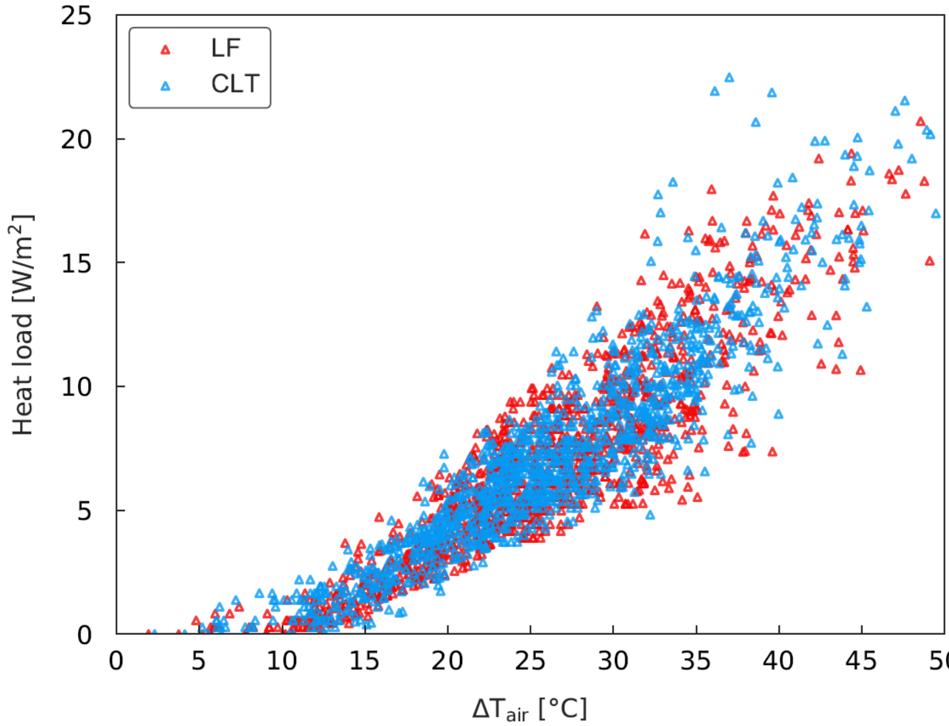


Figure 1.3. Heating load of the building during the heating season (January to April and October to December 2016) as a function of the difference of temperature between indoor and outdoor conditions.

1.3.2 Building use of Domestic Hot Water

As for domestic hot water (DHW), 149.8 MWh/a (49.5 kWh/m^{2}a), or 1.66 MWh per capita, was required. Each occupant asks on average for 58.3 L/day of hot water, for a total annual volume demand of 1,916 m^3. This consumption level is lower than the ones of average Canadians, who use 75 L/day according to [67]. Installments of water-saving devices in the building may have contributed to the smaller hot water demand. Studies have shown in the past that such devices save around 20% of water, which roughly corresponds to the difference observed in the present building [68]. Over the year, the DHW system used 78.2 kWh of energy to heat every cubic meter of water to an appropriate temperature for DHW supply. Calculations of the heat demand required by the ideal DHW system is straightforward:

$$Q_{DHW} = V_{DHW} \rho c_p \Delta T_{DHW} \tag{2.2}$$

where V_{DHW} is the volume of water, ρ, the density (997 kg/m^3), c_p, the heat capacity (4.18 kJ/kgK) and ΔT_{DHW}, the difference of temperature between hot water in the storage tank and water that comes from aqueduct. The value of ΔT_{DHW} is subject to slight variations throughout the year, but can be approximated as being equal to 50°C. Using these values show that the ideal DHW system would consume 57.9 kWh/m^3, which implies that 74% of the energy drained by the DHW system is "useful energy" and that the remaining 26% turns into space heating. At first look, such an efficiency seems poor, but the DHW system efficiency can be as low as 50% in buildings equipped with a recirculation loop [69]. In winter, the waste heat reduces the heat demand, but in the summer, it might lead to overheating. From May to September, which represents the season when heat demand is minimal, a total of 711 m^3 of DHW were consumed by the occupants, requiring 51.4 MWh of energy for the water heating system. Re-using Eq. (2.2), one can estimate that 10.3 MWh (3.2 kWh/m^2) of the DHW system's energy was released within the building as "non-useful" internal heat gain.

1.3.3 Dwellings' individual energy need

Large variations in total energy demand are seen when comparing the energy intensity of each apartment. Fig. 1.4 shows the overall consumption of all dwellings, from the lowest consumer (54.1 kWh/m^2) to the highest (273.0 kWh/m^2). Energy use bars are separated according to the source of their consumption and the energy consumption for heating the air in the ventilation system and for electricity used in common spaces (lighting and HVAC) was separated equally and added to the consumption of all dwellings. Note that the "Ventilation" labeled bars strictly relate to the energy necessary to heat the air in the ventilation system – the energy needed to operate the fans is included in the electricity used for common spaces. For DHW, the volume of water was monitored in the inlet of each apartment and the DHW energy demand was measured for the whole building, so it was possible to convert the volume in energy. The bar labelled “PHPP” represents the energy intensity predicted by the software prior to construction. Only six residential units consumed less energy than projected. In spite of the identical construction, a standard deviation of 53.3 kWh/m^2 between the apartments is observed, with a ratio of five between the highest and lowest consumers. This variability is mostly caused by variations of heat consumption for space heating and DHW – the standard deviation of electricity consumption being less significant. One could theorize that with varying set point temperatures between apartments, it could be possible for a dwelling to receive heat generated in its neighboring apartments, which would increase the differences of consumption between dwellings. However, the internal walls that separate every apartment have a U-value of 0.195 W/m^2K. In a steady-state situation, for a wall of 30 m^2 (the average area of walls separating dwellings), a difference of 5°C in set point temperature between two neighbors would lead to a heat transfer of 29.3 W between the dwellings. Such a heat rate over a heating season corresponds to a total of around 150 kWh. The average space heating consumption of a dwelling in the building is 1,775 kWh, so it would appear that heat shifts between the apartments have a minimal impact and do not explain the large variations observed for heat demand.

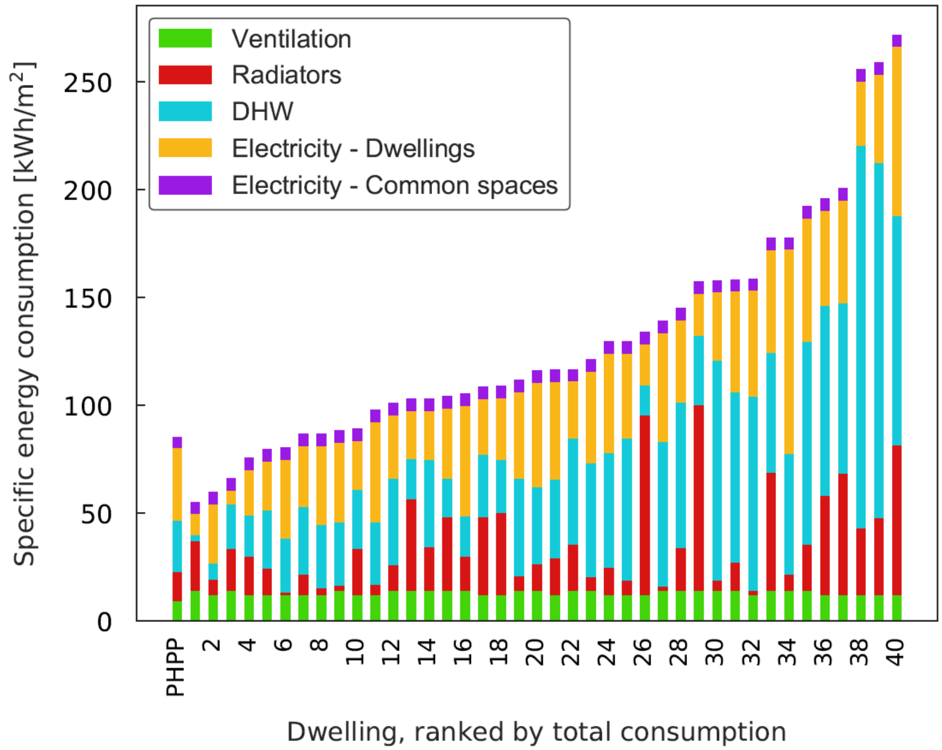


Figure 1.4. Specific energy consumption of the 40 dwellings, ranked from the smallest consumer to the largest.

Although part of the variations in energy demand might be due to dwelling location within the building (e.g., having a south-oriented façade should reduce the needs for heating), most of it is produced by differences in occupant behavior, as found in other monitoring studies performed in apartment buildings [50]–[52]. In fact, Fig. 1.5 shows that the location of the apartment has a minimal influence on its heating demand. It presents in boxplots the distributions when clustering the dwellings heat demand according to a) their floor, b) the orientation of their façade and c) their wall assemblies. Box limits represent the first and third quartile of the distributions, with the midline showing the median value. Whisker lengths are equal to the extreme values or to 1.5 times the interquartile range, whichever is closest to the boxes. These boxplots confirm the large variability observed in heating demand among the dwellings. This variability renders differences observed between the different median values insignificant. For example, the median space heating consumption appears lower in dwellings facing the south, but due to the high variability, it is impossible to declare that the data confirm that dwellings with a south façade consume less heat than the ones with a north façade. The only tangible observation is that dwellings on the first floor have higher consumption that those on higher floors. This finding suggests that the stack effect is present in the building in spite of its air tightness as the pressure balance in the building during winter generates infiltrations (and thus more heat demand) for the first floor and only exfiltrations for the top floor. It could also be explained by the lower U-value of the floor slabs – it is suggested in Fig. 1.2a that important losses of heat happen through the floor slabs. Apartments on the fourth floor are the next larger heat consumer due to the larger area of their envelope that is directly in contact with the exterior. No significant difference can be observed between the overall consumption of dwelling in the CLT section of the building versus those with a light-frame structure.

Figure 1.6 expresses the relationship between a dwelling's energy demand and its household size. One of the dwelling has a household size of five people and was clustered with the 4-people dwellings. A quick regression analysis provide a coefficient of determination $R^2 = 0.005$ for heating, $R^2 = 0.287$ for DHW, $R^2 = 0.050$ for electricity and $R^2 = 0.242$ for total energy consumption. Surprisingly, household size in itself appears to be a weak predictor of DHW and total energy use in a dwelling and insignificant as a parameter to predict heating or electricity demand. The number of occupants living in a dwelling is not the only factor of occupancy that causes differences in energy consumption between identical apartments. It appears that the behavior of the occupants has a larger part to play, for example by demanding different comfort specifications. This can translate into completely different energy demands for space heating, DHW and electricity.

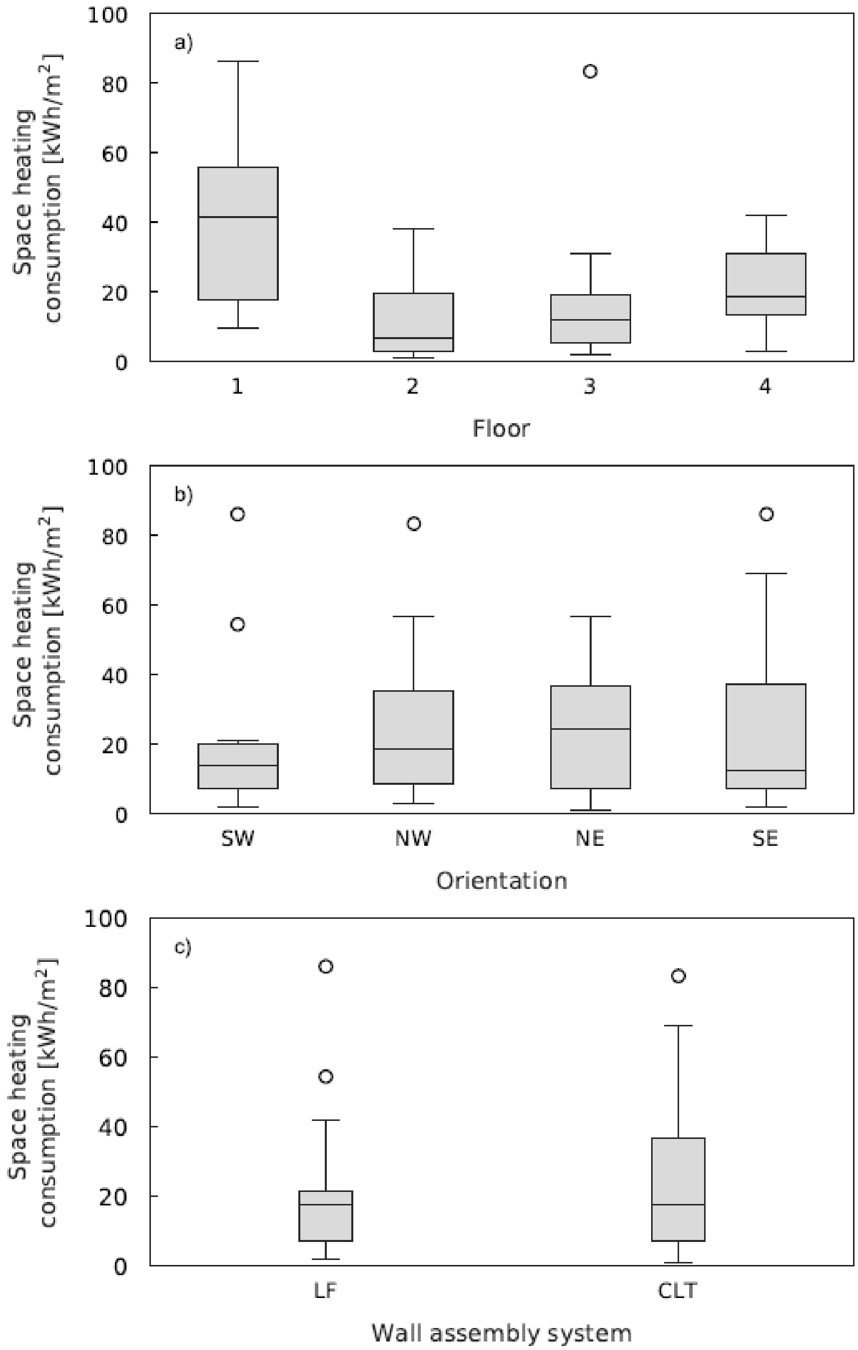


Figure 1.5. Specific heat demand of the dwellings when clustered according to a) their floor, b) the main orientation of their façade and c) their wall assemblies.

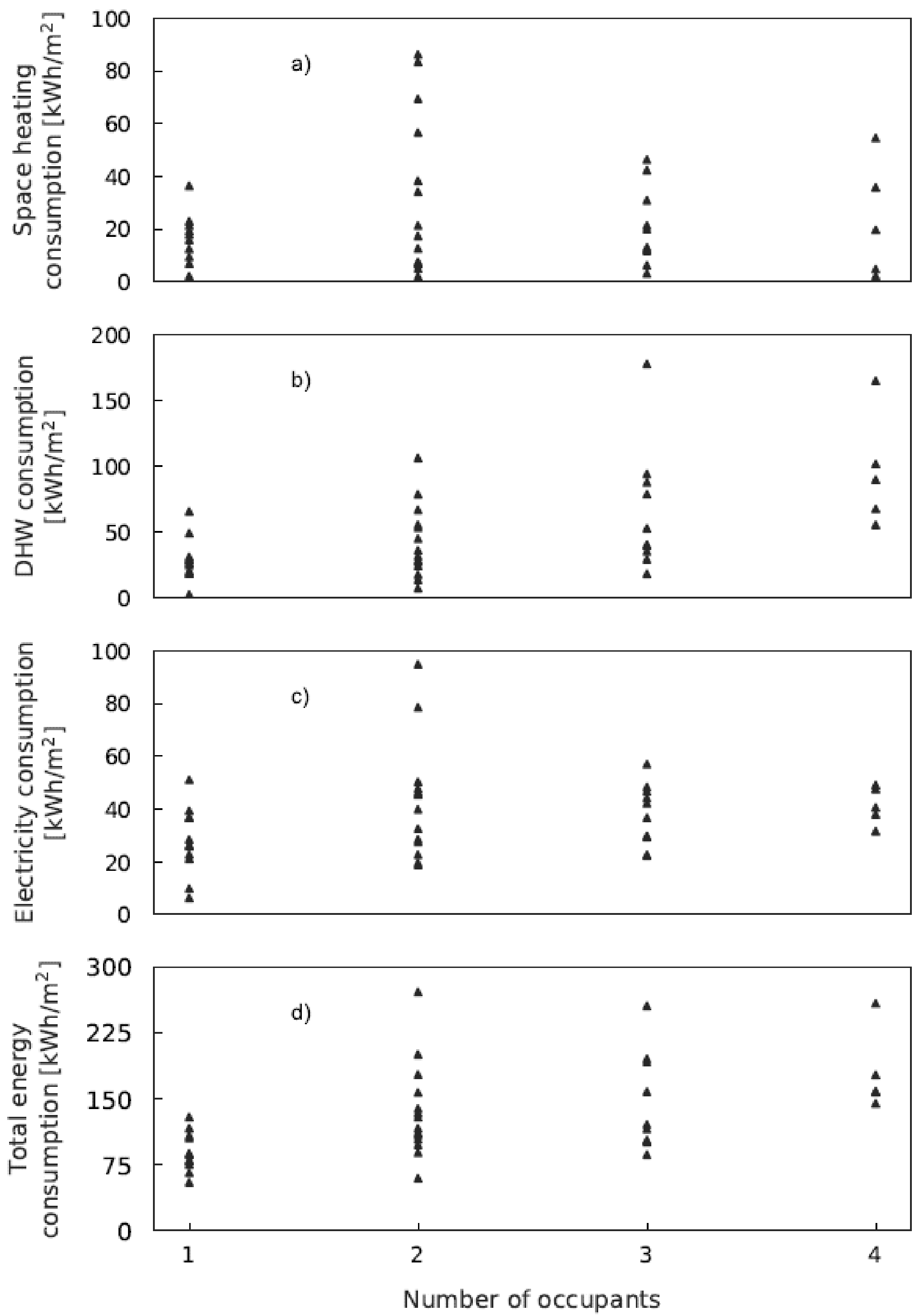


Figure 1.6. a) Heat demand, b) DHW use, c) Electricity use and d) Total energy consumption of a dwelling according to the household size.

1.3.4 Breakdown of energy use

Figure 1.4 not only demonstrated the impact of occupant behavior on energy consumption in dwellings, but it also reveals the great importance of DHW. The high consumption level found for all large energy users is explained by the amount of hot water that they consumed. In fact, 38.3% of the energy demanded by the building was used for DHW whereas space heating drew only 28.6% and electricity, 33.1%. It should be noted however that approximately a quarter of the DHW load likely turns into space heating instead of becoming hot water, as mentioned before. Nevertheless, the proportion of energy used to produce hot water is quite larger than usual. In Quebec, the allocation of energy in the typical apartment is 55% for space heating, 26% for electrical appliances and lighting and 19% for DHW [70]. It appears that the building design elaborated to reduce the space heating load in the case study building was effective, which increased the importance of water heating and electricity in the energy balance. Future work on reducing building energy consumption will need to target more specifically the water heating system.

1.4 *Regression analysis applied to heat demand*

Results displayed in the previous section show significant variability in the heating demand of each of the 40 apartments. These dwellings are identical in terms of envelope and HVAC systems and, except for 1st floor dwellings using more heat, the position of the apartment in the building seems to have a minimal impact on its heating demand. This conveys that actions taken by the occupants greatly influence the energy balance of an apartment. This section uses regression analysis to identify which parameters in the energy balance of a dwelling drive the need for heating. Regression analysis aims to identify the relationship between a dependent variable (here, heating energy consumption) and one or multiple independent variables called *regressors*. In the case of linear regression with M predictors, this relationship takes the form:

$$y = \beta_0 + \sum_{j=1}^{M} \beta_j x_j + \varepsilon \qquad (2.3)$$

where β_j represent the regression coefficients , x_j the regressors and ε expresses the model error, which is the discrepancy between the predicted and observed data. In a well-built regression model, errors follow a normal distribution with zero mean and constant variance and are not correlated with the regressors or with themselves at different time steps. Since the magnitude of β_j depends on the units of measurement of its related regressor, a more robust approach is to scale the model in order to produce standardized regression coefficients [71]:

$$y^* = \sum_{j=1}^{M} \beta_j^* x_j^* + \varepsilon^* \tag{2.4}$$

where:

$$y^* = \frac{y - \bar{y}}{\sigma_y}, x_j^* = \frac{x_j - \bar{x}_j}{\sigma_{x_j}}, \varepsilon^* = \frac{\varepsilon}{\sigma_y}, \beta_j^* = \beta_j \frac{\sigma_y}{\sigma_{x_j}} \tag{2.5}$$

The standardized coefficients β_j^* are also useful to quantify the linearity of a model since in a purely linear model, the summation of the square of the β_j^* coefficients is equal to 1. Therefore, the closest this summation is to 1, the more linear the model is [72]. Estimates of the regression coefficients are usually found by calculating the function that will minimize the least square sum of the errors – a process known as *curve fitting*.

In the reference building, eight apartments were more thoroughly monitored than the others. A multivariate regression function was built for each of these eight apartments to predict the energy consumption of their radiators during the heating season. A time step of one day was taken, meaning that each model is based on 213 observations. Regressors considered to forecast the daily consumption are: the difference of temperatures between outdoor and indoor conditions (x_1 - ΔT), the velocity and direction of wind (x_2 and x_3 – W_s and W_d), the solar radiation reaching the dwelling's windows (x_4 - rad), the opening of windows (x_5 - window), the use of mechanical ventilation (x_6 - vent) and the electricity and DHW demand (x_7 and x_8 – elect and DHW). For x_1, x_2, x_3 and x_5, the daily average value is used. The "opening of windows" variable is represented by the average area of windows which are opened for a day. For example, if a dwelling has four windows of 1.5 m^2 each that are opened for 2 hours in a day, then the average of opened area for the day is 0.5 m^2. When the sensor reads that a window is opened, it is assumed that the window is 100% opened. Regressors x_4, x_7 and x_8 are expressed by the total amount of energy received/used during the day. The quantity of solar radiation reaching the windows of a dwelling were estimated by taking the global solar radiation measured in the weather station on a horizontal plate and converting it to each façade's orientation with the solar angles method [65]. Use of mechanical ventilation is quantified by the number of hours in which the ventilation system was turned on in the dwelling.

It is expected that heat demand will be proportional to the difference of temperature, but inversely proportional to solar radiation. Due to the enhanced infiltration, opening windows should increase heat consumption. Fast winds lead to larger outdoor convection coefficient, increasing heat losses through the envelope as well as infiltrations. Because of the high U-value and air tightness of the walls, the wind's impact is expected to be minimal. Since the set point temperature of the ventilation system is 20°C, heat from radiators would be necessary to raise this temperature level in dwellings with higher indoor temperatures when the ventilation is turned on. Finally, consuming electricity and DHW lead to larger internal heat gains in the building, reducing the energy consumption of the radiators.

The first step to generate the regression model was to visually inspect in scatter plots the relation between regressors and the dependent variable to ensure that a linear regression was an appropriate form. For all dwellings and parameters, no need of using higher-order terms were found – relationships either seemed linear or non-existent. Therefore, the use of Eqs. (2.4) and (2.5) to model heat used by radiators is advisable. The following step was to verify the stability of the regression coefficients by making sure that there was no multicollinearity (i.e. ensuring that regressors are independent from each other). Multicollinearity is likely to be troublesome when the simple correlation coefficient between two regressors exceeds 0.85 [73]. The correlation coefficient between each regressor was computed for all eight models and no high level of correlation between regressors was detected. These preparatory steps revealed that no change was needed in the regression model and that all of the chosen regressor could be included.

Confirming the worthiness of the regression model is essential when comparing the influence of its inputs – a comparison of parameters between inadequate models being meaningless. Four indicators were considered to evaluate the performance of each model.

First is the coefficient of determination R^2, which represents the proportion of variation of the dependent variable that is explained by the regression model. The significance of the models was calculated with the F-statistic test and it was checked that the regression equations were significant 95% of the times. The third indicator is the Durbin-Watson test statistic:

$$DW = \frac{\sum_{i=2}^{n} \left(\varepsilon_i - \varepsilon_{i-1}\right)^2}{\sum_{i=2}^{n} {\varepsilon_i}^2} \tag{2.6}$$

where n is the number of observations in the dataset (n=213 days here). If there is no autocorrelation of 1st order in the model, the expected value of DW is 2. A value of $DW < 2$ means that the model is underfitted whereas the opposite is representative of an overfitted model. Finally, the last performance criterion was examining whether the summation of the square of the β_j^* coefficients was near to 1. A residual analysis to checkup whether errors were normally distributed with a zero mean and a constant variance was also made afterwards.

Table 1.3 provides the standardized regression coefficients produced by the model for each of the eight apartments in addition to model evaluation parameters. Positive coefficients indicate that the dependent variable (i.e. energy consumed by radiators) is proportional to the regressor and inversely proportional for negative coefficients. A t-test was executed to assess the significance of each regressor – bolded coefficients mean that the regressor was deemed as significant by the test. Only the difference of temperatures between outdoor and indoor conditions was considered as significant in all models. Apartments #7 and #8 have no coefficient quantifying the impact of the ventilation system since the switch controlling the ventilation was untouched for the whole year, so it was impossible to evaluate how influential this parameter was. The regression equations obtained in each dwelling yields good performance according to the four indicators, except for apartment #7 which has a poor coefficient of determination. This model also follows unexpected behaviors, such as DHW consumption being substantially more significant than in other dwellings or heat demand arising with solar radiation. Correlation coefficients produced by this model were thus discarded when calculating the average coefficient values found across the different dwellings. These averages show that the parameters that truly drive energy consumption from the radiators are, in order, the difference of temperatures, the consumption of electricity, the opening of windows and the solar radiation. Other parameters are on aggregate less significant. These findings corroborates the results of previous studies as Blight and Coley identified via simulation the first three parameters as being the most important ones that depend on occupant behavior [47] and solar radiation was previously found to be a significant, but not dominant regressor [46].

Table 1.3. Standardized coefficients and model performance indicators for every regression models. Each of the eight residential units have its own specific regression model.

	Unit #1	Unit #2	Unit #3	Unit #4	Unit #5	Unit #6	Unit #7	Unit #8	Average
$\beta^*_{\Delta T}$	**0.957**	**0.582**	**0.772**	**0.920**	**0.751**	**0.93**	**0.712**	**0.867**	0.826
β^*_{Ws}	**-0.080**	0.048	-0.068	0.065	**-0.157**	-0.064	-0.146	0.045	-0.030
β^*_{Wd}	**-0.116**	-0.170	-0.040	0.006	-0.059	0.071	0.056	0.087	-0.031
β^*_{rad}	0.051	-0.087	**-0.296**	-0.101	**-0.248**	-0.027	**0.392**	**-0.203**	-0.130
β^*_{window}	-0.013	**0.632**	0.087	0.124	**0.272**	**0.283**	-0.142	0.034	0.203
β^*_{vent}	**0.098**	-0.068	**0.199**	0.004	-0.040	**0.187**			0.063
β^*_{elect}	**-0.140**	**-0.482**	**-0.405**	**0.167**	**-0.404**	**-0.14**	-0.240	**-0.293**	-0.242
β^*_{DHW}	-0.011	-0.129	0.006	-0.043	0.105	-0.047	**-0.504**	**0.146**	0.004
R^2	0.891	0.790	0.827	0.909	0.843	0.896	0.554	0.933	
F	114.1	9.1	18.5	18.7	14.8	33.2	2.1	31.6	
DW	1.685	2.180	1.886	1.615	1.645	1.922	1.835	1.842	
$\sum(\beta^*)^2$	0.968	1.030	0.902	0.906	0.903	1.012	1.016	0.911	

In Table 1.3, regression coefficients for a given regressor vary from a dwelling to another. For example, $\beta^*_{\Delta T,1} = 0.957$ in the first dwelling and $\beta^*_{\Delta T,2} = 0.582$ in the second. Six clusters were created to determine if these variations were due to the location of the dwelling: a cluster for dwellings with a Northeast façade, one for Southwest façade, a cluster for dwellings in the CLT section, another for those in the LF section, a cluster for 1st floor dwellings and finally a last cluster for dwellings on the 4th floor. The average coefficient values observed in these clusters were computed for the eight regressors and are displayed in Fig. 1.7. Although standardized coefficients are different from a cluster to another, most of these discrepancies are insignificant, demonstrating that the position of the apartment does not considerably affect the regression equation. Two important distinctions, both related to the vertical position of the dwelling, are observed. In dwellings on 1st floor, window openings represent an important predictor of heat consumption, but wind speed has no real influence. In 4th floor dwellings, the situation is reversed – wind speed is critical, but window openings have zero impact. The discrepancy related to window openings might be explained by the stack effect forcing the cold outdoor air to enter the building at the bottom, as previously foreshadowed. Therefore, when opening windows on the 1st floor, outdoor air enters the building without difficulty, thus reducing indoor temperature by rising infiltration. On the top floor, opening windows lead to indoor air leaving the building, which is less harmful in the energy balance. As for wind speed, elevated dwellings are more exposed to the wind and experience heat loss through the roof, so it is not surprising that this regressor is more meaningful on the 4th floor.

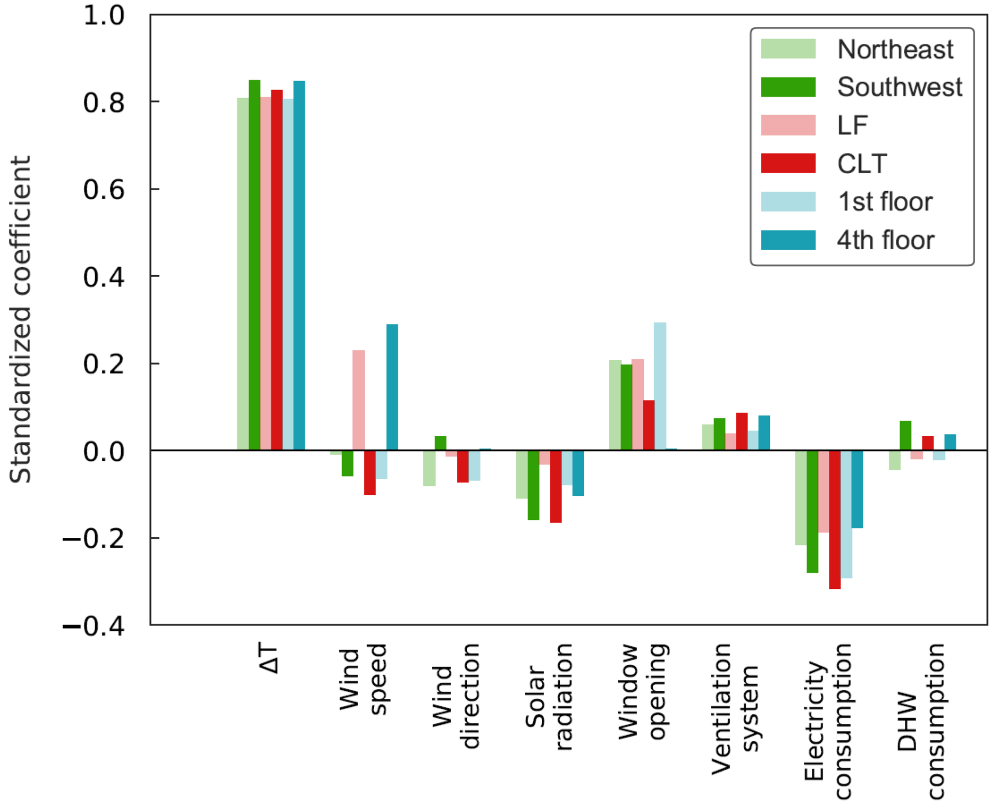


Figure 1.7. Standardized coefficients for each regressor according to the apartment's orientation of façade, wall assembly system and floor.

With the regression models, it becomes possible to estimate the building's potential gain in energy performance by adopting energy optimal occupant behavior. Five of the regressors considered in the models depend on occupant behavior: the indoor-outdoor difference of temperatures (with the control of the thermostat), the control of windows, the control of the mechanical ventilation system and the consumption of electricity and of DHW. Table 1.4 lists the relative change in heat and total energy use given by the models when each of these five regressors are optimized from an energy standpoint. The total energy use is merely evaluated by adding the electricity and DHW demand to the heat consumption predicted by the models. The difference of temperature was minimized by fixing the set point temperature at 19°C, which had a great impact on the heat demand, but a relatively small one on total energy use because of the small part that heating plays in the energy breakdown of the case study building. A similar pattern is observed for keeping all windows closed in winter. Due to indoor air quality issues, shutting down the mechanical ventilation system must be avoid and doing so would only reduce total energy use by 1.7% according the regression models. The minimal electricity consumption profile was determined as being equal to the profile of consumption that yielded the smallest electricity use in the eight dwellings. Evidently, zero use of electrical appliance is the theoretical optimal value, but it is not realistic, hence the use of a real profile. The same procedure was done for DHW. Decreasing electricity consumption increased heat demand by 17.6%, but also reduced overall energy by 23.3%. The most important factors for total energy use are electricity and DHW consumption. Attempts at leading occupants towards energy saving behaviors in high-performance residential buildings should thus focus on these aspects. With the particular energy billing in the case study building, energy price appears as an obvious strategy to influence these behaviors since studies have shown that occupants are more prone to perform energy-saving actions when they are directly responsible for paying energy bills [74], [75]. Feedback with effective building-occupant communication is another promising way to guide people in their buildings [76]–[78].

Table 1.4. Relative change in the average heat and total energy consumption from the eight regression models according to specific changes in occupant behavior.

Change in occupant behavior	Change in average heat demand [%]	Change in average total energy consumption [%]
Indoor temperature set at 19°C	-31.3	-6.55
Windows always kept close	-22.4	-3.71
Mechanical ventilation never operational	-8.9	-1.74
Minimal electricity consumption	17.6	-23.3
Minimal DHW consumption	1.7	-27.4

1.5 *Energy performance gap*

1.5.1 Effects of pre-construction simulation hypotheses

It is mentioned in the previous sections that the case study building was expected to consume 16.6 kWh/m^2 for heating and 74.3 kWh/m^2 in total. In 2016, the actual values were respectively 36.9 and 129.1 kWh/m^2, meaning that the consumption of the building was 122.3% higher than predicted for heating and 73.8% higher for the total energy demand. This energy performance gap might seem large, but is in accordance with figures seen elsewhere in literature [50]. Inputs required for energy simulations are difficult to obtain before the construction of a building (e.g., set point temperatures, weather, infiltration rate…), and need to be estimated. As an attempt to explain the energy performance gap in the case study building, a review of the building model was made in order to find out which hypothesis turned out false and how impactful these erroneous hypotheses were on the energy performance gap.

During this revision, eight modifications were applied to the initial building model. Fig. 1.8 shows the change in heating and total energy demand after cumulatively applying each of these changes to the model. The first modification (denoted M1 in Fig. 1.8) was changing the weather profile to input the measured 2016 weather data. Since 2016 was a warmer year, this slightly reduced the heat consumption. Secondly, the set point temperature of the building was changed from 20 to 23.9°C (M2), which increased heat demand by 63%. The third change was considering window openings in the simulation (M3). Opening windows in winter increases infiltration and thus raises heating demand. In the eight 'super-monitored' apartments, windows were opened 9.4% of the time during the heating season. The uncertainty on this ratio related to the sample size is 12.6% according to the theory of univariate inferential statistics [73]. The total window area of the building is 177.7 m^2, so for the purpose of estimating the energy impact of windows opening, it was assumed that 16.7 m^2 of windows are permanently opened. The amount of air entering the building can be estimated by [79]:

$$\dot{V}_{window} = 0.025 A_{window} U_{wind} \tag{2.7}$$

The average wind speed measured in 2016 was taken in Eq. (2.7). Knowing the amount of air entering the building (1.50 air change of hour), it was then possible to adjust the infiltration rate provided to the software. This methodology was applied since PHPP is a static model, so it is impossible to adjust the infiltration rate at different time steps. Modification 3 raised the energy demand of the building by 11.1 kWh/m^2a.

The heat recovery unit employed on the building was based on a novel technology and did not provide the expected efficiency during the monitored year. The heat recovery was thus decreased from 85% to 70% (M4) - the latter value being provided by the unit's manufacturer. The building population was then reduced from 112 to 90 occupants (M5). The sixth modification is related to the DHW consumption in the buildings. The default volume of DHW use in PHPP is 25 L/day per occupant. This was replaced by the actual amount of water consumed in 2016 that is 58.3 L/day per occupant (M6). Doing so, the energy demand went up by 19.7 kWh/m^{2}a – the most important change seen in Fig. 1.80.9. Circulation of DHW in the building was no accounted for in the initial model – the DHW system was approximated as ideal. The heat loss rate from the pipes of the DHW circulation system was added in the model (M7), enabling estimations on the heat released in the building by the DHW system. This reduces the heat demand since internal heat gains are augmented, but increases the overall consumption due to the waste of energy that happens in the summer. Finally, the last change was supplying the measured electricity use (a total of 42.7 kWh/m^2) of the dwellings instead of using the electricity consumption projections, which were a total of 35.8 kWh/m^2 (M8).

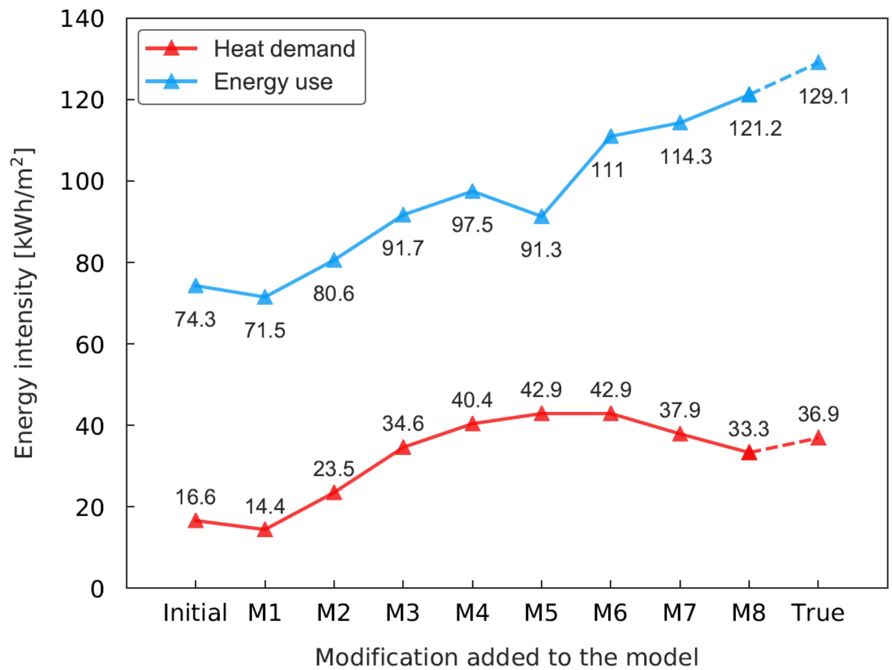


Figure 1.8. Heat and total energy consumption projected by simulation after applying various modifications to correct inappropriate hypotheses made during the initial simulation.

The final building model projects a demand of 33.3 kWh/m^2 for heating and 121.2 kWh/m^2 for total energy, which is closer to the observed consumption than in the original model.

This indicates that other erroneous hypotheses unseen during the model revision accounted for 3.3 kWh/m^2 for heating (energy performance gap of 11%) and 7.9 kWh/m^2 for total energy (gap of 6%), showing that the software can provide relatively accurate results when accurate hypotheses are taken. It is important to note that the building real average indoor temperature and the proportion of opened windows are not exactly known and are merely estimated according to a sample, so there might be errors in modifications M2 and M3 which could increase or reduce the "final energy performance gap". Almost all of the eight modified hypotheses are practically impossible to predict before the operation of a building.

During this exercise, considering the impact of windows opening and adjusting the set point temperature had a great impact on the simulated heating needs of the building. For the total energy, modifications made to the volume of DHW, to window openings and to set point temperatures were the most important. All of these changes are directly related to occupant behavior, demonstrating that building modeling needs an accurate representation of occupant behaviors. This also explains the high differences of consumption seen between all of the apartments in the reference building. Fig. 1.2b displays the building energy flow as projected by the revised model. Note that district heating is now linked with internal heat gains and waste heat due to the consideration of the efficiency of the DHW system. By comparing Fig. 1.2b with Fig. 1.2a, it is possible to see that the major changes between the initial and revised version of the model happened in DHW use (increase of 15.7 kWh/m^{2}a), infiltration (increase of 11.9 kWh/m^{2}a), waste heat generated by electrical appliances and the DHW system (increase of 6.6 kWh/m^{2}a) and mechanical ventilation heat losses (increase of 6.5 kWh/m^{2}a).

1.5.2 Regression analysis applied to PHPP

As discussed, building simulation requires the use of various hypotheses taken by both the modeller and the model. The previous subsection showed that the energy performance gap in the reference building was greatly reduced when more precise estimates are used for the modeling. Here, the performance of the building software itself is studied by applying the regression analysis methodology followed in Section 4 and comparing the outputs of both type of regression models. If PHPP truly replicates the case study building, then a regression equation built from the software should yield the same regression coefficients than those obtained from an in-situ regression model. The same regressors considered in Section 4 were retaken here. Eight distinct PHPP models (each depicting one of the "super-monitored" dwellings instead of the building itself) were created and the regressors were provided to the model as inputs. This generated for each apartment a list containing the estimated heat consumption of the dwelling for every day of the heating season. This list plays the role of the dependent variable in the regression model.

Table 1.5. Standardized regression coefficients when creating the regression model from the dwelling's heat consumption projected by PHPP.

$\beta^*_{\Delta T}$	β^*_{Ws}	β^*_{Wd}	β^*_{rad}	β^*_{window}	β^*_{vent}	β^*_{elect}	β^*_{DHW}
0.862 (4.4%)	0.025 (-183.3%)	0.001 (-96.8%)	-0.165 (26.9%)	0.201 (-1.0%)	0.182 (188.9%)	-0.404 (66.9%)	-0.006 (-250.0%)

As done for the previous regression models, a regression equation was computed for each apartment. PHPP itself being a linear model that highly depends on the regressors considered here, all eight regression equations scored greatly in the four performance indicators. The standardized coefficients of the regression models were calculated and the averages of these coefficients are available in Table 1.5, with the relative discrepancy between these values and those coming from the case study building presented in brackets. Since the eight PHPP apartment models were nearly identical, the differences of the regression coefficients from a dwelling to another were small. The impact of two parameters was well assessed by the software: the difference of temperature and the opening of windows. The latter being well-modeled suggests that the process utilized to convert windows opening in increase of infiltration was accurate. The software appears to severely underestimated the importance of wind and DHW use on the energy balance of the building, but since these regressors are unimportant according to the previous regression models, this underestimation seems to be non-critical. Solar radiation, mechanical ventilation system and electricity consumption all have a bigger influence of the numerical models of the dwellings than on the real dwellings. This observation is not surprising as it is quite difficult to translate solar radiation in solar gains or electricity consumption in internal heat gains.

According to the regression coefficients, the significant variables to determine heat demand in PHPP are the difference of temperatures, the consumption of electricity, the opening of windows, the control of mechanical ventilation and solar radiation. These parameters are the same than those identified from the measured data and ranked in the same order, except for the control of ventilation. In the case study building, this variable was deemed as non-significant on aggregate and its impact is overestimated as mentioned above. Therefore, one could think that for this case study, the equations considered by the numerical software were appropriate to depict a fair representation of the energy behavior of the building.

1.6 *Conclusions*

Forecasting the energy use of a residential building is an important but difficult task. There is often a large gap between a building's predicted and observed energy demand. This paper uses a case study building to increase our understanding of how and where energy is consumed by evaluating the performance of a case study high-performance building with measured data coming from a thorough monitoring. During this evaluation, it was shown that occupant behavior influences greatly the efficiency of a building. Due to the people living in them, identical dwellings may reach substantially different levels of energy demand. This considerable importance of occupant behavior somewhat explains the difficulty of obtaining an accurate prediction of a building's energy consumption. This study showed that it was possible to get a satisfying building simulation from a simple model as long as the occupants in the building are well represented.

For the case study building, the set point temperature and the control of windows were the two variables that justify the most the energy performance gap. Occupants in the building demanded an indoor temperature that was noticeably higher than usual which might be explained by the fact that heating is included in their lease. Preconstruction of the building did not account for the fact that windows are opened during the heating season for more than two hours per day in spite of the cold weather. This action increases infiltration and thus the heat demand as well. It would be beneficial energy-wise to understand the reasons behind these openings of windows and to offer to the occupants solutions to decrease this type for behavior. For example, an occupant might not know that using the mechanical ventilation system is preferable than opening windows in the winter in terms of energy consumption due to the heat recovery. Energy education of occupants could be the next step to take to facilitate the energy efficiency of buildings.

A regression analysis made with the collected data also identified the indoor-to-outdoor temperature difference and windows control as significant parameters for the heat demand of an apartment. Other important variables were electricity consumption, which decreases heat consumption but increases total energy use, and solar radiation. It was demonstrated that the household size, the orientation of the apartment's façade and the type of wall assembly (light-frame versus massive) had minimal influence. However, 1st floor dwellings consume more heat than dwellings on other floor. Part of this is caused by the lesser insulation of the floor slab, but this larger demand is also explained by the stack effect in the building, which seems to be present in spite of the airtight envelope. Another indication of the presence of the stack effect is that opening windows in the first floor leads to an increased heating need whereas this action has no impact in the top floor.

In a typical Canadian residential building, space heating represents most of the energy consumption. However, in the reference building domestic hot water and electricity consumption were more important than heating. As buildings become more and more efficient in terms of envelope and architecture, DHW and plug load will start to play a more important role in the energy balance. In the present case, several solutions were implemented to reduce heat losses, but less attention was devoted to hot water and electricity consumption and to the occupant behavior. This exhibits that to improve energy efficiency of buildings in the future, solutions need to be applied not only for space heating demand, but also for hot water and electricity. Effective communication with the occupants could be an effective starting point for improvements in energy performance.

CHAPITRE 2. ASSESSING THE RISK OF OVERHEATING IN HIGH-PERFORMANCE SOCIAL HOUSING BUILDINGS WITH THE USE OF REGRESSION ANALYSIS

Résumé

Puisque les bâtiments deviennent de plus en plus isolés et étanches, les risques de surchauffe estivale dans les bâtiments sans climatisation sont de plus en plus importants, particulièrement dans un contexte de réchauffement climatique. Les dernières décennies ont montré que la négligence de la surchauffe peut avoir des conséquences fatales. L'inconfort estival doit donc être considéré lors de la conception de bâtiments et de nouvelles stratégies de prévention de ces risques doivent être développées. Des modèles de régression linéaire sont présentés dans cet article et utilisés afin d'identifier les variables les plus importantes pour le risque de surchauffe. Ces modèles se basent sur des données mesurées auprès d'un bâtiment à haute performance énergétique de logements sociaux situé à Québec. Selon les standards de l'ASHRAE, il y a de la surchauffe en été dans les logements malgré les conditions estivales tempérées. Les résultats de la régression linéaire suggèrent que les occupants peuvent par eux-mêmes réduire l'intensité de la surchauffe par 53% en minimisant leur consommation d'électricité et d'eau chaude, en prévenant le rayonnement solaire d'entrer dans leur logement ainsi qu'en maximisant l'utilisation des systèmes de ventilation.

Abstract

As households are getting more insulated and airtight to reduce energy consumption, overheating in free-running buildings is quickly becoming an issue during summer, especially considering climate changes. Unfortunately, recent history has shown that overheating can quickly lead to wide-scale fatalities. Thus, summer discomfort should be considered when designing buildings and new strategies to prevent overheating should be developed. In this paper, a regression analysis is applied to build household models from measured data that can be used to identify the most important weather, building and occupant parameters on the risk of overheating. This data comes from a monitored high-performance social housing building in Quebec City, Canada. According to ASHRAE's adaptive thermal comfort model, overheating was found to occur in spite of the relatively mild summer conditions. Results from the regression analysis suggest that occupants can reduce by 53% the intensity of overheating by reducing their electricity and DHW consumption, by preventing solar radiation from entering the built environment and by constantly using ventilation systems.

2.1 *Introduction*

Lack of preparations regarding uncomfortable summer indoor conditions in free-running buildings can have fatal consequences. For example, the 2003 European heatwave led to a death toll of nearly 15,000 in France alone, corresponding to a staggering increase of 60% of the mortality rate for that time of the year [80]. Due to climate changes, more frequent and intense heatwaves are expected in the future, thus increasing the risk of mortality due to overheating. Moreover, the rise of super-insulated and airtight buildings that rely on natural ventilation to cool indoor air in summer could add to this problem if no proper strategy is brought to evacuate solar and internal heat gains. Therefore, it is crucial to properly evaluate thermal comfort in free-running households during the summer and to ensure that applicable standards are respected.

This paper evaluates with a regression analysis the risk of overheating in a high-performance social housing building in the climate conditions of Quebec City, Canada. Data coming from the monitoring of eight dwellings located in a case study building allowed the development of multivariate regression models that predict indoor temperature in summer according to the weather and to the behavior of the occupants. Based on ASHRAE's adaptive thermal comfort model [81], the study used the regression models to find ways to improve the summer thermal comfort in the case study building.

2.2 *Case study building*

The reference building is a monitored social housing building of 40 dwellings with a total floor area of 3,024 m^2 (32,550 ft^2). It was built in 2015 in Quebec City, Canada. Quebec City is located in ASHRAE's very cold climate zone (zone 7A). A particularity of the building is that it is composed of two distinct symmetrical sections that use different structural systems. In the northwest section of the building, wooden light-frame wall assemblies (LF) was used whereas the southeast section employs massive timber panels (cross-laminated timber (CLT)). The airtightness of the envelope and the thermal resistance of the vertical walls are the same. Therefore, from a thermal standpoint there are only two differences between the two sections: first, the roof is more insulated in the LF section with a resistance of RSI-9.37 (R-53) versus RSI-7.27 (R-41) for the CLT section and second, the presence of massive panels in the CLT walls highly increases the thermal inertia of this section.

Since the building was constructed with the objective of limiting energy consumption, it has a compact geometry in addition to a very insulated and airtight envelope. The thermal resistance of the vertical walls and of the windows are respectively RSI-6.35 (R-36) and RSI-0.87 (R-5). Near the southwest façade of the building, deciduous trees provide shading in the summer, and yet allow solar gains in the winter. The building consumed 36.9 kWh/m^2 for heating in 2016, which is twice as small as the average new construction in Quebec [82]. The conditioning of air in the summer relies on natural ventilation as no mechanical cooling was installed. The total surface area of the windows is 177.7 m^2 (1,913 ft^2), which is nearly 6% of the total floor area and thus respects the minimal natural ventilation requirements of 4% of ASHRAE 62.1. The maximum depth that is naturally ventilated is 4.33 times higher than the floor-ceiling height, which also respects natural ventilation requirements (maximum ratio of 5). Altough no cooling is provided, occupants control the on/off switch of a 100% fresh air mechanical ventilation system that has a capacity of 100 m^3/h (59 cfm) per dwellings – a value that is equal to the one prescribed by ASHRAE recommendations to ensure acceptable indoor air quality [83].

The thermal environment of the eight dwellings located in the eight corners of the building was monitored. In these dwellings, the air temperature and relative humidity in all rooms were recorded by the control system, in addition to the electricity and DHW consumption, the state of the mechanical ventilation system (on/off), the state of all windows (on/off) and the temperature on the indoor wall surface. Combined with air temperature, the latter allows the calculations of the dwellings' operative temperature. Data presented in this paper covers the period from June 1st 2017 to October 1st 2017, roughly representing the summer season. Data are logged every 10 minutes, except for the window states which are measured every minute. Hourly weather data for the covered period of time was obtained from a weather station situated nearby.

2.3 *Overheating assessment*

The thermal comfort in the case study building during the summer of 2017 was evaluated according to the adaptive thermal comfort model, which is incorporated in ASHRAE 55. This method is based on the notion that occupants react to restore their comfort when a change occurs to produce thermal discomfort. Therefore, it is only applicable for occupant-controlled naturally conditioned spaces and all four of the following criteria must be met:

1. There is no mechanical cooling system,
2. No heating system is in operation,
3. Occupants are free to adapt their clothing and the built environment (e.g., opening windows),
4. The prevailing mean outdoor temperature T_{pm} is greater than 10°C (50°F) and smaller than 33.5°C (92.3°F). T_{pm} is the exponentially-weighted running mean temperature of the last month. The weights give more importance to the daily temperature of the more recent days (ASHRAE Standard 55 suggests to employ weights decreasing from 0.9 to 0.6 [81]).

As previously stated, there is no mechanical cooling in the case study building and since people are free to do what they want at home, the third criterion is also respected. The few timesteps in which the heating system was activated were withdrawn from this analysis. Finally, it was verified that the prevailing mean outdoor temperature is between the range prescribed in the fourth criterion between June 1st 2017 and October 1st 2017. Consequently, the adaptive model is applicable for the case study building during the desired period. This model defines upper and lower allowable indoor operative temperature T_{in} limits (T_{max} and T_{min}) that are given by a single linear equation based on T_{pm}. The centre point of these bounds is considered as being the "ideal" operative temperature T_{comf} according to T_{pm}. Figure 2.1 offers a visual depiction of the adaptive comfort theory.

From this model, three discomfort parameters (D_{freq}, D_{int}, D_{avg}) were used in this paper to measure thermal comfort. D_{freq} assesses the frequency of overheating and is merely equal to the number of hours during the summer in which the indoor temperature was above T_{max}. D_{int} represents the intensity of overheating and is calculated by using the cooling degree-day method with a base temperature of T_{max}. D_{avg} is the average difference between T_{in} and T_{comf} calculated over the summer. If this parameter is above zero, then it means that the indoor air is generally warmer than the ideal environment. If it is below zero, then it could be considered too cool.

Table 2.1. Assessment of overheating in summer in eight residential units according to their wall assembly, their floor level and the orientation of their main façade.

Cluster	**Overall average**	**Overall standard deviation**	**CLT**	**LF**	**1st floor**	**4th floor**	**Northeast façade**	**Southwest façade**
D_{freq} [h]	388	444	654	122	159	617	461	315
D_{int} [h°C]	224	311	394	54	54	394	267	181
(h°F)	(403)	(559)	(709)	(96)	(97)	(708)	(480)	(325)
D_{avg} [°C]	2.17	0.75	2.63	1.71	1.98	2.36	2.34	2.00
(°F)	(3.91)	(1.35)	(4.74)	(3.08)	(3.57)	(4.25)	(4.21)	(3.60)

Table 2.1 reports the calculated values of the discomfort indices for the 8 monitored dwellings when clustered in separate groups that account for their wall assembly, their floor level and the orientation of their façade. As can be seen, according to these discomfort parameters, the indoor environment was warmer in dwellings located in the CLT section than in those in the LF one. The temperature in the CLT section was on average 2.63°C (4.74°F) above T_{comf} and it exceeded T_{max} for 654 hours. For the LF part of the building, these numbers are respectively 1.71°C (3.08°F) and 122 hours. These differences could be explained by the thermal differences between the two types of wall assembly or simply by the fact that the CLT section is more oriented towards the south. However, according to Table 2.1, the apartments that have a southwest façade are cooler than those with the northeast façade, no matter what structural system is used. Apartments on the fourth floor have higher discomfort parameters than those on the first floor. This could be due to the stack effect which brings warmer air in the upper part of the building and to the fact that dwellings on the fourth floor are more exposed to solar radiation since their ceiling is directly connected with the outdoor. The presence of the ground can also serve as a heat sink for the first floor dwellings, hence their cooler indoor environment. Due to the sample size, tests of significance were done to see if the differences observed between the clusters could be explained by randomness (mostly generated here by differences in occupant

behaviors) or not. The tests conveyed that the differences between the CLT and LF dwellings (p-value of 0.003) and between the 1st and 4th floor dwellings (p-value of 0.054) were statistically significant, but that the one related to the orientation of the façade was not (p-value of 0.287).

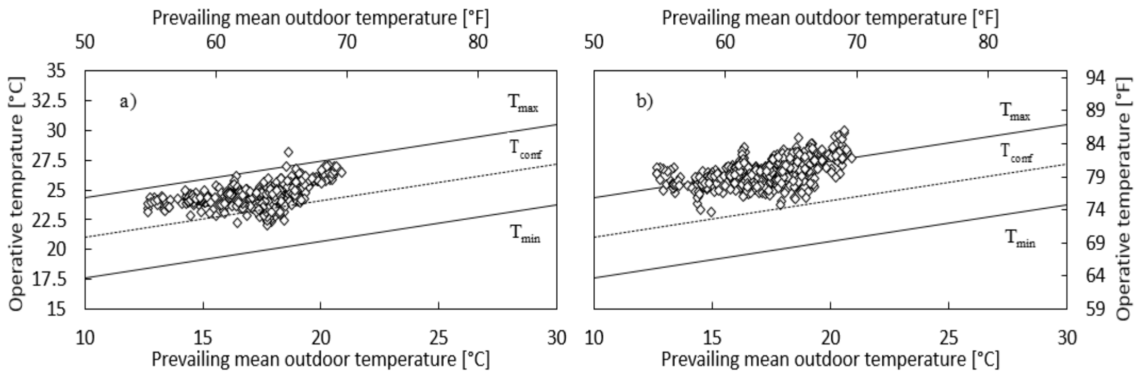


Figure 2.1. Comparison between the indoor temperature and the acceptable range prescribed by ASHRAE Standard 55 for a) the coldest dwelling and b) the warmest dwelling.

Figure 2.1 presents in a scatter plot the relation between the indoor temperature in the coldest and warmest apartments during the summer and the mean prevailing outdoor temperature. The dots in Fig. 2.1 were taken every six hours. As mentioned earlier, Fig. 2.1 also draws the acceptable temperature ranges and ideal temperature in accordance with the adaptive method. It can be seen that in the warmest apartment, many points of the scatter plot are located outside of the acceptable range. Even in the coldest dwelling, T_{in} is above T_{comf} most of the times. This proves that overheating is occurring in the case study building.

An interesting point found during the evaluation of overheating in the building is that, aggregated over the eight dwellings, T_{in} was superior to the outdoor temperature 97.29% of the times. Moreover, although T_{in} was above T_{comf} 97.19% of the times, the outdoor temperature exceeded T_{comf} only 7.05% of the times, showing that the outdoor conditions offer a good potential for heat evacuation. From an overheating standpoint, it thus appears advantageous to allow the transfer of air and heat between the indoor and outdoor environments. The ventilation system was activated in the eight apartments 51.8% of the time and windows were opened 52.1% of the time. Increasing these values could potentially decrease the overheating problems found in the case study building.

2.4 *Regression analysis model*

As discussed in the previous section, overheating in dwellings depends simultaneously on several variables, such as the location of the dwelling in the buildings or the wall assemblies forming the dwellings. Occupant behavior, along with the weather, also have an important role to play in the energy balance of a building. Consequently, it is difficult to tangibly quantify the impact of each of these aspects. Multivariate regession analysis can address this problem since the objective of such analyses is to find the relationship between a response variable (operative temperature in this case) and one or multiple predictors. With a proper regression model, it becomes possible to understand how the response variable reacts to each of the predictors. When the timestep of the model is an hour or lower, it is advisable to develop a dynamic model to account for thermal inertia. A linear combination of the predictors and past values of the response variable is thus sought to express the current state of the response variable:

$$y(t) = \beta_0 + \sum_{i=1}^{M}\sum_{j=0}^{\tau}\beta_{ij}x_i(t-j) + \sum_{j=1}^{\tau}\alpha_j y(t-j) \tag{3.1}$$

where τ is the number of previous time periods to be included, β_{ij} are the regression coefficients linked to each predictor x_i, and α_j are regression coefficients added to account for the inertia of the response. To account for the fact that the magnitude of β_{ij} varies greatly from a predictor to another due to the units of measurement, it is suggested to use standardized coefficients in order to improve the robustness of the model:

$$y^* = \beta_0^* + \sum_{i=1}^{M}\sum_{j=0}^{\tau}\beta_{ij}^* x_i^*(t-j) + \sum_{j=1}^{\tau}\alpha_j^* y^*(t-j) \tag{3.2}$$

where:

$$y^* = \frac{y-\bar{y}}{\sigma_y},\ x_i^* = \frac{x_i-\bar{x}_i}{\sigma_{x_i}},\ \beta_{ij}^* = \beta_{ij}\frac{\sigma_{x_i}}{\sigma_y},\ \alpha_j^* = \alpha_j \tag{3.3}$$

Here, $\bar{k}$ is the mean value of variable k over the period of the analysis and σ_k its standard deviation. Two different types of multivariate regression functions were developed. The first one is a unified model which incorporates the data found in all eight monitored dwellings into a single data matrix. The objective of this model is to provide a quantitative estimation of the impacts of each predictor on the operative temperature. The second type of regression models developed is an indoor temperature model specific to each dwelling that can be used to simulate “what if” scenarios. Simulations made in this paper will evaluate the potential of overheating reduction that occupants have in their dwellings. Generating a specific function for each dwelling will increase the models accuracy and thus should improve the simulation results. However, since some predictors, such as the dwelling location, remains unchanged throughout the summer, it would be impossible to evaluate their impact on the response variable with individual dwelling models, hence the need of a unified model along with the individual ones. All models used a timestep of one hour and a lag period of $\tau = 6$ hours. Preliminary analyses showed that this combination yielded the best results in terms of accuracy and computational times. To fit with the desired timestep, T_{in} was switched from 10-min to hourly time series merely by averaging the temperatures during each hour.

The predictors considered in the models were the outdoor temperature T_{out} (x_1), the prevailing mean outdoor temperature T_{pm} (x_2), the outdoor relative humidity (x_3), the velocity and direction of wind (x_4 and x_5), the solar radiation entering the dwelling (x_6), the cooling rate induced by natural and mechanical ventilation (x_7) and the consumption of electricity and domestic hot water (x_8 and x_9). For the unified model only, three dummy variables were added as predictors to represent the wall assembly (x_{10}, 0 = LF, 1 = CLT), the floor level (x_{11}, 0 = 1st floor, 1 = 4th floor) and the orientation of the façade (x_{12}, 0 = NE, 1 = SW). Solar radiation entering the dwelling was estimated from the weather station’s measurements using the solar angles method [65]. The sensible cooling rate is estimated in Wh for any timestep with this equation:

$$C_{vent} = \left(f\dot{V} + 90A_w W_s\right)c_p\left(T_{in} - T_{out}\right) \tag{3.4}$$

Air volumetric thermal capacity c_p is considered constant at 0.33 Wh/m^{3}K (0.018 BTU/ft^3°F). f is the fraction of time in which the mechanical ventilation system was operational for the dwelling, $\dot{V}$ the airflow from this system when it is enabled, A_w the average surface area of opened windows during a given timestep and W_s the average wind velocity during the timestep. The equation used to evaluate the amount of air entering through the windows came from [79]. Before starting the regression analyses, a visual inspection with scatter plots was made to make sure that linear regression was appropriate to represent the relationships between predictors and the response variable. It was also ensured that predictors are independent from each other since multicollinearity can be troublesome for the stability of the model if the simple correlation coefficient between two predictors is above 0.85 [73].

The data set was divided in two distinct periods of time: a training period that ranges from June 22th to October 1st and a validation period (June 1st to June 21st) to ensure the accuracy of the indoor temperature forecasts. A Matlab script was given all the data concerning the predictors and response variable during the training period and used curve fitting to find the optimal set of regression coefficients β_{ij}^* and α_j^* that minimizes the least square sum of each model's errors. For the validation period, the individual dwelling models were given the true indoor temperature during the six hours that preceded the initial timestep and then had to find T_{in} for the whole period while using their own computations of the temperature at the previous time steps. This procedure was chosen because the objective behind these models is to simulate the change in indoor environment after modifying the time series of the predictors. Therefore, the true indoor temperature becomes invalid as the simulated temperature becomes different from the real one. The goal of the unified model merely being to quantify the impact of each predictor, the validation of this model could be done with the true indoor temperature being provided to the model. Fig. 2.2 shows how the resulting predicted temperature curves compared with the measurements for the individual dwelling models. These models were able to follow adequately the behavior of the true indoor temperature. In the least accurate model, the average magnitude of prediction errors was 0.57°C (1.03°F). Over the eight models, the mean bias error was -0.08°C (-0.14°F), showing that the models have a very slight tendency of underestimating T_{in}. As for the unified function, since it received information concerning the true temperature, its computations were closer to measurements than the ones obtained with the individual dwelling models. The average error for this model was 0.22°C (0.40°F). Overall, it was deemed that the simulations results were good enough to qualify the models as validated.

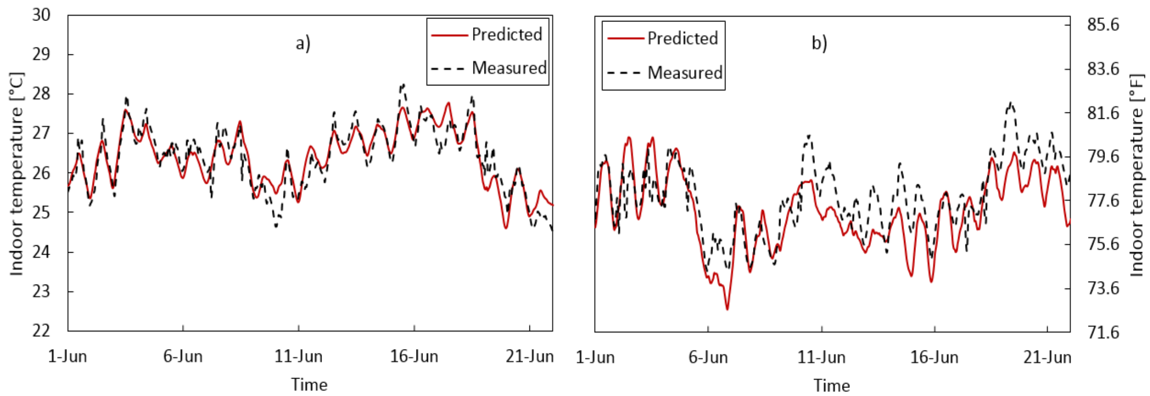


Figure 2.2. Comparison of simulation from the individual dwelling models and measurements results for the indoor temperature during the validation period for a) the most accurate model and b) the least accurate model.

To assess the impact of each individual predictor in the estimation of the indoor temperature from the unifited tool, all of their related regression coefficients were summed to create a new variable that indicates the weight of each parameter in the estimation of T_{in}:

$$\omega_i = \sum_{j=0}^{\tau} \beta_{ij}^* \text{ and } \omega_{Tin} = \sum_{j=1}^{\tau} \alpha_j^* \tag{3.5}$$

The weights calculated from the unified regression model are displayed in Fig. 2.3. The weight of the indoor temperature during the preceding timesteps is not presented since it massively dominates other predictors – considering the 1-hour timestep of the models, the indoor temperature at a given timestep is always very close to the preceding one. From Fig. 2.3, it can be seen that (other than the previous indoor temperatures), the most important parameters are the outdoor temperature, the type of wall assembly forming the envelope of the dwelling, the use of ventilation, the consumption of electricity, the floor level of the dwelling, the solar radiation and the quantity of hot water that is used in the dwelling. A test of significance deemed these predictors as being significant, whereas the outdoor relative humidity, the prevailing mean outdoor temperature and the wind velocity and direction were found to be insignificant parameters. A positive weight signifies that the response variable increases when the prediction is increasing. For instance, consuming electricity leads to a warmer dwelling whereas opening windows decreases the indoor temperature. Fig. 2.3 is in agreement with Table 2.1 in that the type of wall assembly and the floor level of a dwelling are significant parameters affecting the indoor temperature.

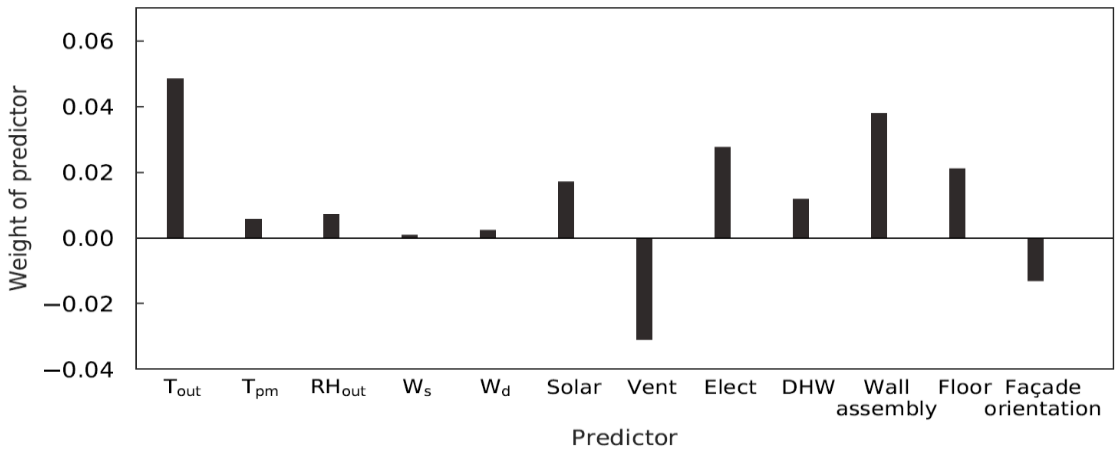


Figure 2.3. Weight of all predictors on the calculations of the indoor temperature.

2.5 *Fighting overheating*

Out of the nine predictors considered in the regression analysis, four are related to the occupants (at least to some extent): the solar radiation entering the dwelling, the cooling rate through ventilation and the electricity and DHW consumption. The former two parameters also greatly depend on external conditions that are not controlled by the occupants, but people can still affect their values with the control of blinds and windows for example. A multiplication factor that ranges from 0 to 200% was individually applied to the inputs of the four mentioned parameters in the indoor temperature simulation models. Fig. 2.4 presents the influence of these parameters on the average discomfort parameters found in the eight dwellings. From the figure, it is quite clear that ventilation has a very significant impact. According to the models, completely shutting off the windows and ventilation system would increase the average frequency of overheating from 388 to 676 hours. On a lower level, electricity and DHW consumption and solar radiation are also important parameters – the frequency of overheating is almost linearly proportional to these inputs. Therefore, to reduce overheating, one could prevent solar radiation from entering the dwelling as much as possible, reduce the consumption of electricity and hot water and in particular, the utilization of mechanical and natural ventilation should be maximized.

The potential reduction of overheating that occupants can achieve by adopting a thermally optimal behavior was assessed with the individual dwelling models. This optimal behavior has the maximal ventilation rate (windows and fans are always opened) along with the lowest possible solar radiation (all radiation blocked by blinds) and electricity and hot water consumption (the consumption profiles of the dwelling that consumed the lowest quantity of electricity and hot water was inputed). From the regression functions, such a behavior leads to an average of 166 hours of overheating in the eight dwellings with an intensity of 105 h°C (189°F). The average environment was on average 1.15°C (2.07°F) above T_{comf}. Compared to the values obtained in the real building, the simulated occupant behavior led to a reduction of 57.2% of overheating in terms of frequency, of 53.1% in terms of intensity and of 1.02°C (1.84°F) for the average indoor temperature. In spite of the fact that all simulated dwellings had the same occupant behavior, variations of overheating are still seen between the apartments. The fourth floor dwellings are still warmer than those on the first floor, with a frequency of overheating of 281 hours during the summer in the 4th floor and of 52 hours on for 1st floor apartments. CLT apartments also have higher overheating factors than the LF ones. With the optimal behavior, there are 298 hours of overheating in CLT-dwellings with an intensity of 194 h°C (349 h°F). As for LF apartments, these values respectively go down to 35 hours and 16 h°C (30 h°F).

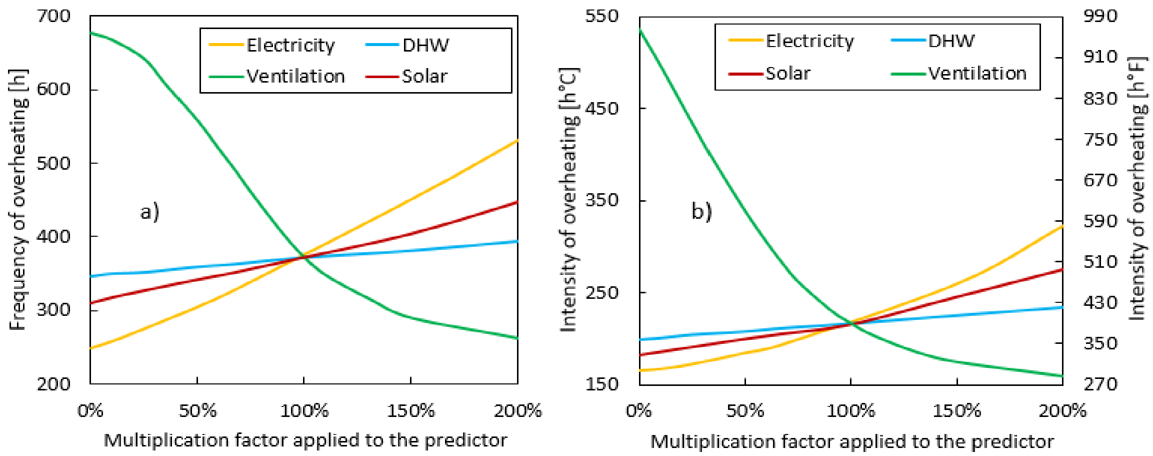


Figure 2.4. Impact of the four predictors related to occupant behavior on a) the frequency of overheating and b) the intensity of overheating.

2.6 *Conclusion*

With the use of three discomfort parameters, this paper studied the overheating in a free-running high-performance residential building located in Canada. It was found that overheating is present in most of the dwellings of the building. Since it is usually warmer inside the dwellings than outside, the great insulation and airtightness could explained this overheating, along with the relatively limited use of ventilation by occupants. Regression analysis identified that the most important parameters for the evolution of the indoor temperatures in the building are, in order, the outdoor temperature, the type of wall assembly, the cooling rate via ventilation, the electricity consumption, the floor level of the dwelling, the solar radiation and the use of hot water. An optimal behavior could diminish by half the overheating problem.

CHAPITRE 3. ADAPTING STOCHASTIC OCCUPANT BEHAVIOR MODELS INTO A UNIFIED TOOL FOR MULTI-RESIDENTIAL BUILDINGS IN CANADA

Résumé

Une stratégie pour combiner des modèles stochastiques d'occupation, de demande en eau chaude et de consommation d'électricité disponibles dans la littérature est présentée. L'outil centralisateur ainsi développé se base sur des modèles développés aux États-Unis, au Royaume-Uni et au Canada. Or, il y a des différences de comportement des occupants entre ces trois pays, d'où l'emploi de facteurs d'échelle se basant sur des statistiques nationales. L'outil génère d'abord l'horaire d'occupation des logements simulés, puis base ses prévisions pour les horaires de demande en eau chaude et de consommation d'électricité sur ce profil d'occupation. Le modèle est validé avec un bâtiment de logements sociaux qui contient 40 unités de logement dont la consommation d'eau chaude et d'électricité fut répertoriée. La validation montre que l'outil peut produire des profils réalistes de consommation. Toutefois, il y a toujours certaines différences entre les prévisions et la réalité, suggérant ainsi des idées de recherche futures pour améliorer la modélisation du comportement des occupants.

Abstract

A strategy to combine existing stochastic occupancy, domestic hot water (DHW) and electricity load models initially developed for different countries is presented. The proposed strategy uses scale factors that refer to national aggregated data to adapt the behaviors represented by the models from a country's lifestyle to another. The technique introduced in this paper is used to create a unified occupant behavior simulation tool for Canadian social housing buildings. This tool first generates an occupancy schedule for the simulated dwellings and then bases its forecasts of DHW and electricity load profiles on this generated schedule. The tool refers to American and British models and it was found that there are differences in behavior between Americans, British and Canadians, hence the need of scale factors. The tool was validated with a social housing building that contains 40 residential units from which the domestic hot water and electricity consumption was monitored. The validation showed that the tool can produce realistic profiles since it is mostly in agreement with consumption patterns found in the monitored building. However, there remain discrepancies which suggest potential research ideas for future work in occupant behavior modelling.

3.1 *Introduction*

Up to 40% of the global energy demand comes from buildings [1], in part as a result of inefficient design, construction and operational practices. Although low energy design and construction approaches have achieved some success, it is known that poor operational practices could compromise design performance targets by a factor of at least two [85]. Reduction of energy consumption therefore needs to come not only from using improved design and construction technologies, but also from recognizing the impact of occupant behavior [3][4]. Yet, despite detailed investigations of occupant behavior and its impact on energy demand [88]–[90], in practice it is still scarcely considered in building modeling.

Users' actions affecting building performance include the presence of people (occupancy), the use of electrical appliances, the use of domestic hot water (DHW) appliances, the use of lighting, the control of the heating system, the control of window openings, the control of blinds, etc. At present, the industry normally uses static schedules to represent these actions in energy simulations, even though more advanced occupant behavior models have been developed over the years. With such an approach, for a given number of individuals using a specified building, the amount of heat, DHW and electricity used at a given time is fixed and known and corresponds to an "average" expected behavior [8][9]. In reality, different individuals have different preferences and hence adopt different behaviors. Consequently, for a given number of occupants there is a quantifiable range of possible energy consumption levels for a building instead of the single value obtained with static schedules. Hence, it is not surprising that great differences are often observed between the predicted theoretical consumption of a building and its actual energy demand (the so-called "energy gap"), most frequently due to occupant behavior [93].

Another way to depict occupant behavior in building simulations is with the use of stochastic models [94]–[97]. Since these models are based on probabilities instead of a purely deterministic approach, they allow the representation of more realistic and diverse occupant behaviors. These stochastic models allow new ways of performing building designs. For example, Ramallo-González et al. initiated the concept of robust optimization of low-energy buildings [98]. These variations lead to different levels of consumption of heat, DHW and electricity and thus can capture the wide range of possible annual energy demand of a building.

Most of existing stochastic occupant models were built upon country dependent data [99]–[101]. As occupant behavior depends on socio-economic and psychological factors, cultural differences can lead to different occupant behaviors, implying that occupants in different countries might act differently [12][19][20]. Consequently, most existing occupant behavior models cannot be employed straightforwardly all around the world. One solution to this problem would be to replicate in each country the extensive monitoring process required for the development of these models in order to obtain country-specific calibrated models. Sometimes, the required data is readily available in databases [104], but this is not the case for most countries such as Canada. Despite the evident reliability and precision provided by extensive field surveys, it should be recognized that this approach is also quite cumbersome since surveys are very time-consuming and expensive to perform.

Another important limitation is that most occupant behavior models found in the literature have been developed independently. For example, a building professional may use an occupancy schedule model to predict the occupancy in the simulated building and then use a different tool for the use of DHW - the resulting outputs will likely contradict themselves as the two models are disconnected. For example, there might be a probability that there will be a shower taken in time steps when no occupant is present. Merging all these models together would create coherent profiles. It is substantially easier for users to employ one unique model instead of relying on multiple ones based on various methodologies that employ different nomenclatures.

This study investigates the potential and limits of an approximate and “unified” model that would represent multiple occupant behaviors in multi-residential Canadian buildings, based on the strategy of merging recognized occupant behavior models from different countries and introducing coherent scaling and diversity factors. The actions considered are:

1. Occupancy, i.e. presence in dwellings.
2. DHW appliance use.
3. Lighting and electrical appliance use.

The model generates time-series profiles for each of the considered behaviors using a time step of 10 minutes for a specified number of dwellings. The generated profiles are consistent with each other. The model is implemented in MATLAB [105]. The tool was primarily developed with the idea of representing occupant behavior in energy simulations of multi-residential buildings at the predesign or design stage, which dictated the required level of details and accuracy. The model could also be used for other applications, such as for predictive control, demand-side management or during the sizing of HVAC systems. For example, a methodology to size the DHW system in an apartment building was developed based on an occupant behavior model (see Chapter 5). The following section details the methodology employed to build the integrated occupant behavior model and Section 3 discusses the limits of the approach that was used and the validity and precision of the model by comparing its outputs with independent measurements obtained from a multi-residential building in Quebec City, Canada.

3.2 *Occupant behavior model*

This section presents the proposed methodology to develop the occupant behavior model that is tested in this paper. Three behaviors are predicted by the model for Canadian dwellings: the occupancy of the building, the DHW consumption of its users and their electricity consumption. Each of the predicted behaviors interacts with each other to ensure that the generated outputs are consistent. The scheme in Fig. 3.1 exhibits the relationships between these behaviors. The number of dwellings and the number of days must first be specified. Other important parameters such as energy price, socioeconomical status and appliances' ownership are already considered in the probabilities functions used within the model. The proposed model will be confronted to real monitored data later in this paper to verify to what extent it was able to predict occupant behavior.

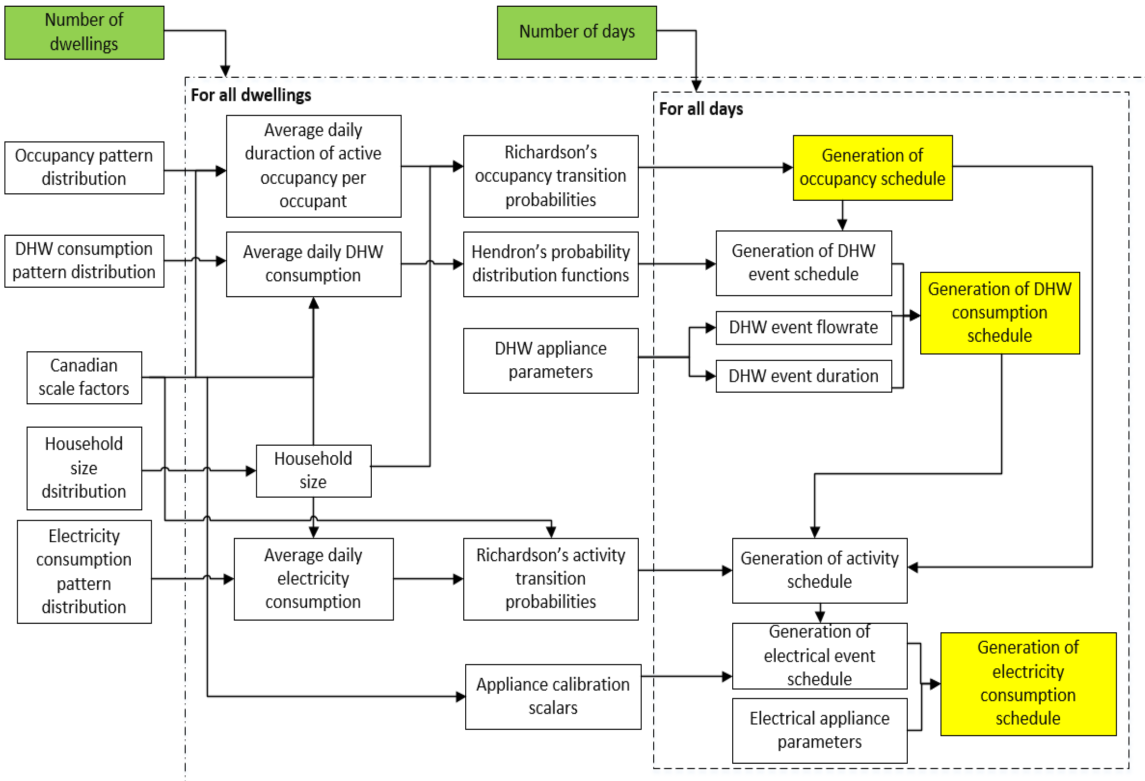


Figure 3.1. Architecture of the occupant behavior model showing the relationship between all components. Green boxes refer to inputs that have to be provided by the model user. Yellow boxes are the outputs of the model.

3.2.1 Active occupancy model

The initial step of the model is to find when occupants are active in their home. For its high simplicity, the stochastic daily occupancy profiles generator developed by Richardson *et al.* [99] was chosen to serve as the basis for the active occupancy model. Active occupancy is defined here as the periods when an occupant is physically active in their house (not sleeping). During this period, the occupant is not necessarily interacting with the built environment but has the capacity to do so. Richardson's model employs first-order Markov-chain Monte Carlo method [106]. Since it is of the first order, the number of active occupants at a given time step depends only on the number of active occupants at the preceding time step, the day of the week, and the hour of the day. Richardson's tool uses a 10-minute resolution, meaning that there are 144 time steps in a day. The probability of changing from one state to another is different for each of these time steps. These probabilities are logged in “transition probability matrices” that are based on a survey of 20,000 weekly UK household journals [107].

Three additions to Richardson’s model were incorporated in the present occupant behavior model. First, the possibility of allowing the model to choose the household size of each simulated dwelling was included. In Richardson’s tool, the user must provide the household size. In the present tool, the household size can be generated randomly based on a probability distribution of the given country (in our case from Canadian household statistics [108]). Note that this step is not mandatory if one already knows the household size of the dwellings.

The second adjustment modifies Richardson’s model to represent occupancy in a country that is different from the one for which the model was originally created (in this case, United Kingdom). Researchers have developed occupancy models that are similar to Richardson’s in the US [109], Spain [110] and Sweden [111]. The center for Time Use Research in Oxford have uploaded data files that contain time use information from dozens of countries [104]. However, for some of these countries (Canada being one of them), the available time use information provides the amount of minutes spent by citizens on various activities, but not the starting time of these activities. It is thus impossible to find with that data precisely at what time occupants were actively at home, preventing the replication of Richardson’s methodology to create occupancy simulator for those countries. However, it is possible to compute the aggregated daily amount of time during which a person is actively at home. Knowing this data for two countries, it is possible to calculate a scale factor to adapt an occupancy model developed in the first of these two countries to the lifestyle of the second one. Referring to the case of the UK, time-use survey overviews say that British citizens spend on average 1,003 minutes per day in their home and sleep for 476 minutes, meaning that they are actively living in their dwellings for 527 minutes per day [107]. In Canada, these numbers are 990 minutes at home, 498 minutes of sleep and consequently 492 minutes of active occupancy was used in this study [112]. Therefore, Canadians spent on aggregate 35 fewer minutes per day awake at home than British – an average reduction of 6.6% of active occupancy. Obviously, for this scaling approach to be appropriate, one has to assume that the lifestyle in the two countries considered is not too dissimilar.

Any time a random number is drawn to find the number of active occupant for the next time step, the number is multiplied by a scale factor that ensures that occupancy respects national aggregated data. The model was run 1,000 times after the application of this scale factor for a household during a weekday and a weekend day. This number of simulations was chosen based on the work of McKenna *et al.*, who showed with a similar model that negligible variations of aggregated results are found after 1,000 simulations [113]. It showed that active occupancy lasts for 473.0 minutes during weekdays, 539.2 minutes during weekend and thus as expected 492.0 minutes per day on average. This scaling methodology relies on the assumption that apart from the total time of active occupancy, people from different countries are likely to follow similar occupancy patterns when their ways of living are similar. It is clear that the assumption that the occupancy pattern in a country can serve as the basis for developing the occupancy pattern in another country might not be true if the two countries are too dissimilar. Evidently, when one would already have access to TUS data or to a specific occupancy model for the country of interest, it would be preferable to refer to this data. However, when such detailed information in unavailable, the proposed methodology could be considered, and in that case, the scaling is a simple and convenient way to adapt the occupancy profiles with the available information.

The final modification accounts for diversity in occupancy patterns between different households. Families have different needs and live through different situations, meaning that some households tend on average to stay at home more often than others. To reproduce this “dwelling-to-dwelling” variability, the model employs a probability distribution to assign an average daily occupancy duration per person to each dwelling. The probability distribution assumes that the average amount of time spent at home for a dwelling follows a normal distribution. The mean of the distribution is set to one so that its introduction in the model will not affect the aggregated occupancy. The standard deviation was computed with results from Aerts *et al.*, who found that people who are mostly absent from home spend approximately 240 minutes per day at home while those mostly at home stay there 720 minutes when they clustered households in seven distinct groups according to their occupancy profiles [114]. This work was made in Belgium, where the average active occupancy is 493 minutes per day [114], a value that is essentially equal to the one in Canada. The standard deviation of 114 minutes was chosen for the normal distribution so that the range of values agrees with Aerts' data. This standard deviation is equal to 23% of the mean value. Therefore, for every household, the scale factor in the model is multiplied by a random parameter which follows a normal distribution with a mean value of $\mu = 1$ and a standard deviation of $\sigma = 0.23$.

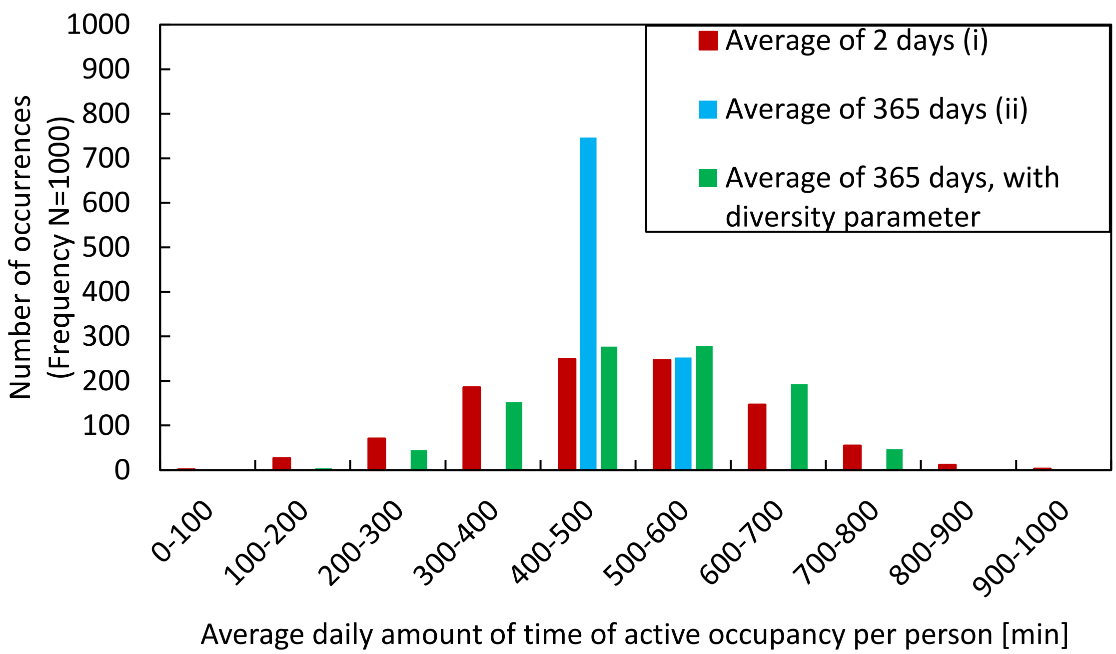


Figure 3.2. Distribution of the average daily amount of time of active occupancy per person in 1,000 simulated dwellings according to different models.

The methodology was used to obtain annual profiles for 1,000 dwellings. Fig. 3.2 plots the resulting distribution of average daily active occupancy duration per person in these dwellings, and compares it to two other simulation strategies that do not employ a distribution to infer "dwelling-to-dwelling" diversity: (i) simulating one weekday and one weekend day and replicating them over a year and (ii) simulating 365 days without inducing diversity between the households. The latter option leads to a very narrow distribution that is not close to the target "dwelling-to-dwelling" diversity. Taking this option means that every simulated household will follow identical aggregated occupancy patterns. The "simulating two days" solution tends to overrate the diversity of occupancy as a non-negligible proportion (10.7%) of the dwellings are outside the desired range of diversity. Because only two days are simulated, this strategy is more sensitive to abnormal days, hence the large variability. This option yields a standard deviation of 148 minutes per day, which overestimates the target of 114 minutes by 29.8%. These observations are based on the assumption that the probability distribution used in the model to enforce diversity in occupancy patterns is accurate.

3.2.2 Domestic Hot Water (DHW) model

Few stochastic DHW models that generate volumetric consumption are available in the literature [17][34][35]. Most of the DHW models are integrated in thermal-electrical domestic demand models that compute the thermal demand for DHW. These models use a range of methods such as non-homogeneous Markov chains [32][36][37], time-series [119], probability density functions [97] or neural network [120] to predict the heat demand due to the consumption of water. Yet, they are not coupled with occupancy and electricity use, which can limit their applicability, particularly in cases where the use of DHW and electricity have a certain level of interaction (for example, houses in which the DHW is generated by electricity).

A popular and easy-to-use model is the yearly DHW event schedule generator developed by Hendron *et al.* [100], [121]. This model generates an annual volumetric DHW profile for a single dwelling by dividing DHW consumption into five types of water appliances (shower, bath, sink, clothes washer and dishwasher). Each appliance has a daily probability density function (PDF) that determines the probability that the appliance is involved in a hot water event at each hour. These PDFs were computed with datasets coming from two monitoring studies in the United States [121]. When the model predicts a hot water event, the volumetric consumption is calculated by multiplying the duration of the event with the flowrate at which water is consumed. These two variables are randomly chosen according to different PDFs that are specific to the five hot water appliances. This model is based on data coming from one country and, like Richardson's occupancy model, might not adequately represent the DHW demand patterns in other countries.

Six modifications were implemented to adapt Hendron's model for the tool developed in this paper. First, a linear interpolation was made to adjust the hourly resolution of the start-time PDFs needed to the 10-minute time steps of the model. Second, a calibration scalar is added to account for the household size. There should be more hot water events in dwellings that have large household size and vice versa. A slope of 35 litres per person, divided within the five appliances, is used for this calibration. This slope is equal to the value used by the Canadian building simulation software HOT2000 [122].

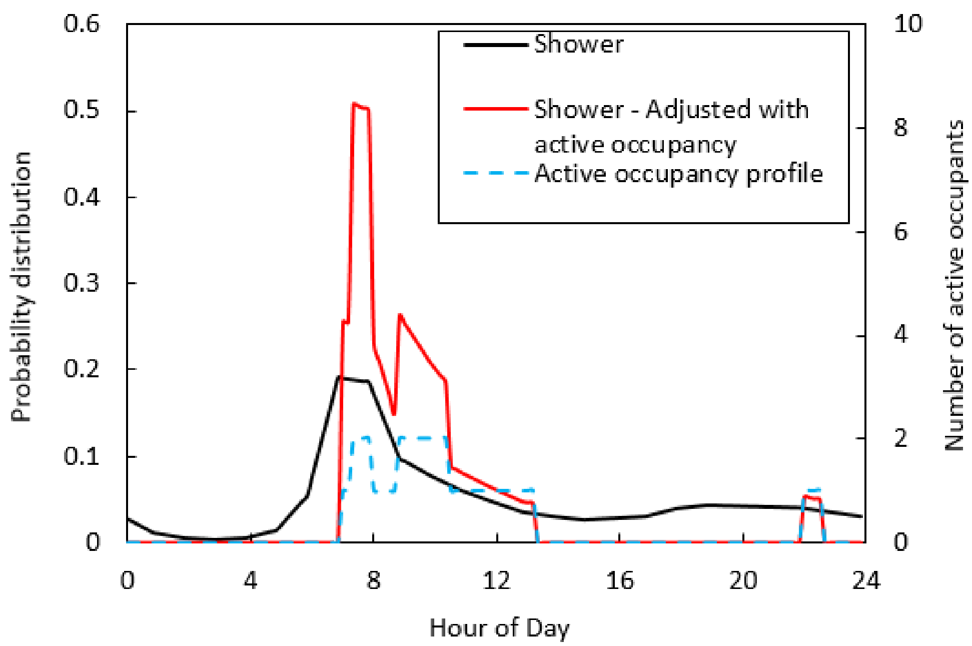


Figure 3.3. Modification made to the probability density function of a shower event to account for active occupancy.

The third modification is linking DHW consumption to occupancy. The shower, bath and sinks cannot use DHW when there are no occupants awaken in the building. In addition, there should be more DHW consumption when there are many active occupants in the dwelling. Therefore, for all time steps, the PDFs are multiplied by the projected number of active occupants to accentuate the probability curves in time steps with high occupancy.

The area under the curve of the new PDFs must be equal to the initial ones to ensure that the aggregated amount of daily DHW use is unaffected by this change. The modified functions are thus multiplied by a correction factor that is equal to the ratio between these two areas. Fig. 3.3 offers a graphical example of this procedure for the probability of using the shower during a single day. The aggregation achieved by simulating 1,000 different days is shown in Fig. 3.4. If active occupancy (blue curve) had no influence, the probability curve before the fitting with occupancy (black curve) would perfectly be superimposed with the aggregated function generated after the fitting (red curve). The morning peak in the aggregated PDF happens an hour later than in the previous function, probably due to the British origins of the occupancy model versus Hendron's tool which was developed for the USA. In the evening, since it is the peak period for active occupancy, there is an increase in the probability of a shower event. The integration of the black and red curves provides identical values, demonstrating that this treatment is only affecting the timing of events and not the overall quantity of events.

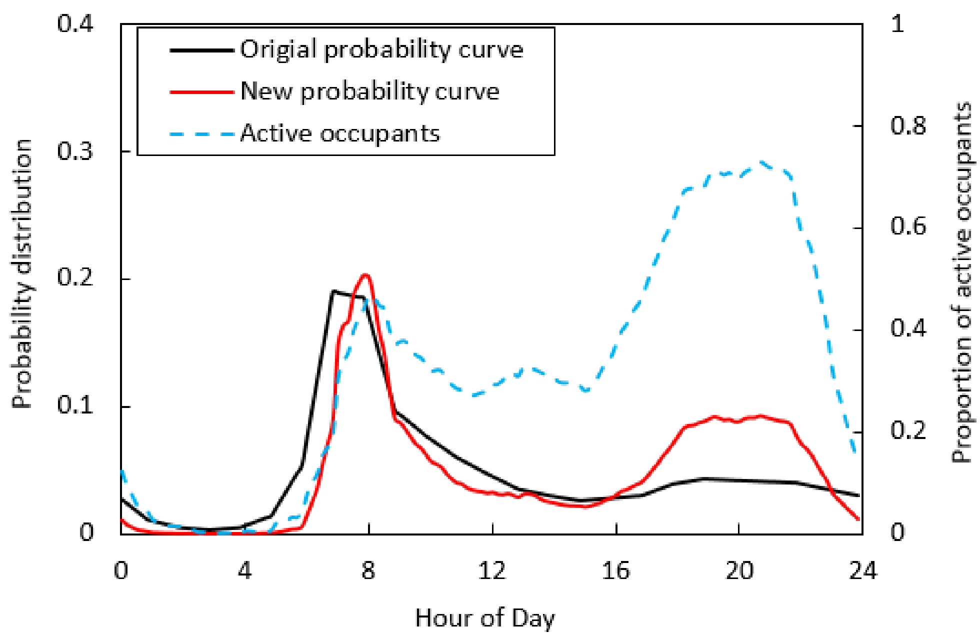


Figure 3.4. Aggregated start-time probability density function for the shower before and after accounting for active occupancy.

The fourth adjustment scales Hendron's model from American to Canadian data (see Table 3.1). A scale factor reduces the PDFs that are used for the duration of hot water events since Americans and Canadians have slightly different DHW consumption levels. The fifth modification is another scale factor that decreases the flowrate to account for low-flow devices (showerheads, dishwashers, washing machines and sinks) that are getting more widespread. A reduction factor of 20% was selected based on an analysis of retrofits in [123]. This factor is applied to all appliances except for the bath.

Table 3.1. Aggregated daily DHW use per dwelling for five water appliances [67][100][124].

Hot water appliances	**Canadian data [L/day]**	**American data [L/day]**
Shower	59	73
Bath	40	18
Sink	81	65
Clothes washer	36	24
Dishwasher	9	15
Total consumption	225	195

The sixth and final change to Hendron's model is the consideration of diversity in the level of consumption between dwellings. To do so, a scalar is drawn from a "diversity" PDF that is based on a monitoring study [68]. This study provides the distribution of daily DHW consumption of 119 households, ranging from an average of 12.5 L/day to 612.5 L/day with a mean value of 172.0 L/day. Part of that variability is due to the number of occupants forming these households, but the study also gives the distribution of occupancy in the monitored dwellings in addition of a best fit equation to find the average daily DHW consumption in L/day from the household size:

$$V_{DHW} = 39 \times \#Occ + 17 \quad (4.1)$$

where #Occ is the number of occupants living in the dwelling. By combining this best fit equation with the occupancy distribution, it is possible to find what the distribution of DHW consumption would be if every occupant asked for the same volume of water. Fig. 3.5 compares this "household size based" distribution with the one actually measured in the 119 homes. It is clear that the measured distribution is larger than the one predicted strictly with the household sizes – more dwellings have an average consumption below 100

L/day and above 300 L/day. This is suspected since people have different habits and some use more DHW than others for various reasons such as ecological or financial concerns, minimal use of the dwelling and different comfort requirements. A random parameter has to be applied to Eq. (4.1) to simulate this aspect. Different distributions were tested and it was found that the log-normal distribution with a mean of $\mu = 0$ and a standard deviation of $\sigma = 0.35$ provided the best fit between the generated DHW consumption distribution and the one measured in the study. The average output of a log-normal distribution with $\mu = 0$ is 1 so this introduced parameter does not change the predicted aggregated volume of water. Therefore, in the model, each dwelling received a 'diversity' parameter from this distribution which is multiplied by the duration of hot water events to calibrate the total volume consumed by the household. This modification changes the average volume of water used per event, but not the number of events itself, i.e. heavy DHW users are considered in the model as people taking long showers, not as people taking many showers. The frequency of hot water events is already linked with the number of occupants living in the dwelling.

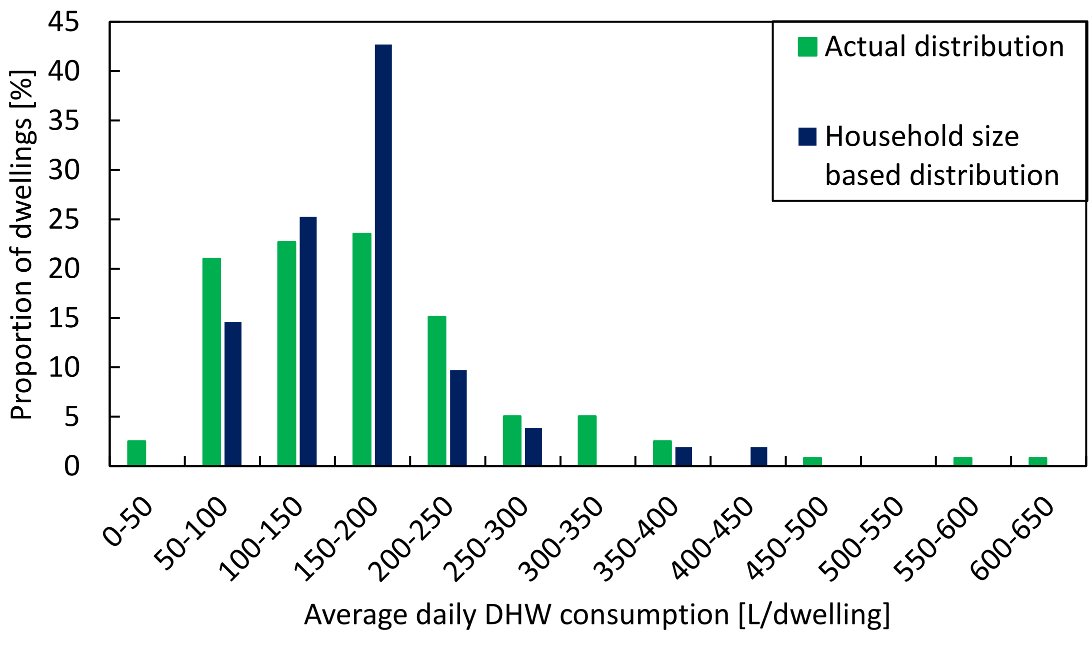


Figure 3.5. Comparison of the measured density of average daily DHW consumption with the one generated by only considering household sizes.

3.2.3 Electricity model

Several residential electricity consumption models have been created to predict the intensity and timing of demand and peaks. Some models rely on financial aspects (price of electricity, household income, appliance ownership) [125], other use weather data (temperature, precipitation) [126] or the type of occupants (age, gender, education) [127] to generate electricity demand profiles. "Economic" models often run into the problem of combining aggregated economic data with disaggregated load profile data, hence the recent gain in popularity of "non-economic" models that prefer to use time-use surveys as their basis [36][47]–[49]. Two of these time-use surveys based models are the ones developed by Richardson [101] and Armstrong [131], which were both taken in this paper to simulate the electricity consumption. Since it is already connected with the active occupancy model, Richardson's was taken to generate schedules for the use of electric appliances, as these schedules greatly depends on active occupancy. As for Armstrong's model, it was employed for the usage of the lighting systems. Armstrong's model has the advantage (in the context of this paper) of being based on Canadian lifestyle. Using two distinct models for the generation of electricity consumption profiles will reveals whether it is possible to combine two models that are based on different modeling methodologies to adequately simulate electric demand in households.

Like his occupancy model, Richardson's electricity use tool relies on the Markov-Chain technique, an efficient way to model the use of electrical appliances as these appliances have two possible states (on/off), hence their popularity in electricity forecasting models [11], [27], [51]. In time-use based electricity models, Markov chains create daily schedules of activities in a building by identifying the times at which occupants switch from an activity (cooking, laundry, watching TV…) to another. The transition probabilities between these activities were computed from time-use survey data, as in his active occupancy model. Every individual appliance is linked to an activity so that its likelihood of being used increases once the corresponding activity is ongoing in the generated activity schedule. Contrary to Hendron's DHW model, when an appliance is seen as being activated, it is used for a constant duration with a specific power consumption since no data could be found on the variability of the duration of use of the electrical appliances considered in the model. Future iterations of the model could include this detail.

Once again, Richardson's model was scaled to fit with Canadian lifestyle so the tool can be validated with the data available for this specific work. Table 3.2 lists the aggregated amount of time that a Canadian spends on cooking, on watching TV and on household work [112]. Differences are observable between this data and the ones found in time-use surveys made in the UK [107]. The activity probabilities are multiplied by a scale factor to ensure that the aggregated results are identical to the left column of Table 3.2.

Table 3.2. Daily amount of time spent on various household activities for the average person [107][112].

Activities	Canadian data [min]	British data [min]
Active occupancy	492	527
Cooking	42	37
Watching TV	126	85
Household work	73	57

Table 3.3 contains the list of appliances that make up the model shown in this paper. Out of the 33 electrical appliances that are considered in Richardson's tool, some were taken off. *Chest freezer*, *Fridge freezer* and *Upright freezer* were merged in one single appliance named *Freezer*. Likewise for *Tumble dryer* and *Washer dryer* which became *Dryer*. *Answer machine, Cassette Player, Clock, VCR/DVD player*, *Cordless telephone*, *Fax* and *Printer* were eliminated as they either are devices that are rarely seen in dwellings today or that consume a negligible amount of energy. *Small cooking (group)* was divided in multiple end-uses: *Toaster, Exhaust fan* and *Coffee Maker*. Moreover, all appliances related to electric domestic water or space heating are not considered since this model is about the non-HVAC electricity consumption of residential buildings. Two additional devices were introduced: *Laptop computer* and *Hair dryer.*

The activity *None* in Table 3.3 means that the appliances do not require active occupancy to be operating. For devices that are associated with *Occupant*, there has to be at least one active occupant in the dwelling for them to be turned on. The C*lothes washer* and *Dishwasher* appliances are simulated differently since they are linked to *Domestic Hot Water*. The DHW part of the model directly identifies time steps in which these appliances are used, so there is no need for calibration scalars. The rest of the activities are the ones considered by Richardson and are simulated with the activity probabilities matrix: *Watching TV*, *Cooking*, *Laundry*, *Washing/Dressing*, *Iron and House cleaning*. The probabilities of use provided in Table 3.3 describe the likelihood that an appliance is operating once its corresponding activity is enabled in the activity schedule. For example, when the *Cooking* activity is happening, there is a probability of 17.2% that the hot plate is used by the occupants. For their calculations, the total number of hours of operation per year has to be computed:

$$D_i = \frac{1000E_i - 8760P_{off,i}}{P_{on,i} - P_{off,i}} \quad \text{for } i = 1, 2..., m \tag{4.2}$$

where E_i is the aggregated energy consumption in kWh measured in Canadian homes found in Table 3.3 for appliance i, $P_{on,i}$, its power consumption when operating and $P_{off,i}$, the standby consumption. Inserting proper numerical values in Eq. (4.2) gives, for example, a use of 168.3 hours per year for the hot plate. Knowing this duration, it is possible to find the annual number of events:

$$M_i = \frac{60D_i}{\lambda_i} \quad \text{for } i = 1, 2..., m \tag{4.3}$$

where λ_i is the event length in minutes. Continuing with the example of the hot plate, which was attributed an event length of 16 minutes, the model must produce an average of 631 events per year. To obtain the probability that people use the hot plate when cooking, the total number of time steps in which the *Cooking* activity is activated is needed:

$$N_j = \frac{365\delta_j \times 2.4}{\Delta t} \quad \text{for } j = 1, 2..., n \tag{4.4}$$

Here, δ_j represents the daily aggregated amount of time spent on activity j and Δt the model time step. δ_j is multiplied by 2.4 because according to the household size distribution, the mean household size is 2.4 occupants per dwelling. For the *Cooking* activity, Canadians cook 42 minutes per day, meaning that in the average dwelling, there is cooking for 100.8 minutes per day (36,792 minutes per year). With a time step of 10 minutes, this translates for the model into 3,679.2 time steps in which *Cooking* should be enabled. The probability that the hot plate is operating when cooking is merely the ratio between the targeted amount of hot plate events and the number of *Cooking* time steps:

$$P_i = \begin{cases} \dfrac{M_i}{N_j} & \text{if } j = \text{on} \\ 0 & \text{if } j = \text{off} \end{cases} \tag{4.5}$$

Hence, a probability of use of 631 / 3679.2 = 17.2% for the hot plate. The same procedure was repeated for all appliances to get the parameters displayed in Table 3.3.

As previously mentioned, Armstrong's electricity model, which is based on probability density functions, was used to simulate the consumption of the lighting systems. Each season has its own daily probability curve to calculate the odds of a lighting event happening. Evidently, use of lighting greatly depends on multiple building aspects, such as its localization and orientation, its window-to-wall ratio or the shading of the surrounding buildings. For the sake of simplicity, these aspects are not considered in these PDFs. When a lighting event occurs, the power consumption varies between 60 and 410 W and the duration of the event is selected between 5 and 120 minutes. The modification made to Armstrong's model was to adapt the PDFs so they fit with occupancy profiles. The treatment applied to Hendron's tool to account for occupancy was repeated for the probability curves of lighting events.

For each dwelling, a scale factor is applied to the 'probability of use' parameters for electrical appliances. This factor is the product between three sub-factors: one that is due to household size $s_{\#Occ}$, another for the type of consumer $s_{consumer}$ and a final one to consider the type of building $s_{building}$:

Table 3.3. Specifications used by the model for each appliance to compute their operating schedule and energy consumption [64][101].

Appliance	Activity	Operating Power [W]	Standby power [W]	Event length [min]	Probability of use	Annual consumption in Canada [kWh/year]	Annual consumption in the UK [kWh/year]
Refrigerator	None	265	0	20	0.1902	801	87
Freezer	None	263	0	20	0.1916	614	277
Desktop computer	Occupant	250	5	300	0.0023	749	247
Laptop computer	Occupant	130	0	300	0.0016	156	-
Stereo	Occupant	120	9	60	0.07858	153	80
Coffee maker	Occupant	900	0	3	0.1330	130	-
Kettle	Occupant	1500	1	3	0.1662	225	157
Lighting [141 m^2]	Occupant	-	0	-	-	2030	715
Dishwasher	DHW	467	0	35	-	94	91
Clothes washer	DHW	505	1	30	-	99	149
TV 1	Watching TV	100	3	73	0.0631	99	236
TV 2	Watching TV	100	3	73	0.0635	99	140
TV receiver box	Watching TV	40	2	73	0.1104	63	128
Exhaust fan	Cooking	250	0	30	0.2035	90	-
Hot plate	Cooking	1250	1	16	0.1715	219	128
Microwave	Cooking	1500	2	30	0.0658	197	66
Toaster	Cooking	1200	0	3	0.2598	58	-
Range	Cooking	1600	3	43	0.1950	770	145
Dryer	Laundry	4115	1	45	0.8892	1284	80

$$S_{dwelling} = S_{\#Occ} \times S_{consumer} \times S_{building} \tag{4.6}$$

The number of occupants sub-factor was estimated with data taken from Statistics Canada suggesting that the relation between electricity consumption and household size has a slope of approximately 3.75 kWh/day per occupant [133]. As for the type of consumer, the data used in Armstrong's model mention report that low-energy detached houses in Canada consume approximately 13.2 kWh/day, while this value goes up to 35.6 kWh/day for heavy consumers. Unfortunately, since studies on the diversity of electricity consumption between different people are rare, it was not possible to isolate the variations of consumption that are due to the household size. Applying the methodology used to determine diversity in active occupancy, the range between 13.2 and 35.6 kWh/day corresponds to a normal law with a mean value of 24.5 kWh/day and a standard deviation of 5.6 kWh/day. The standard deviation is equal to 22.9% of the mean value, and therefore for each dwelling a normal distribution with $\mu = 1$ and $\sigma = 0.229$ drives the value of the 'type of consumer' sub-factor. Once again, the distribution's unitary mean value ensures that this sub-factor does not affect aggregated results. A minimum of zero is set for this parameter so there cannot be negative consumption. Since this prescribed minimum is more than three standard deviations away from the mean, the distribution is not visibly truncated and the effect of this constraint on the mean output is negligible. The 'type of building' parameter is there to adapt the energy demand for apartments. All data related to electricity used so far were representative of consumption in detached single houses. Since the electricity consumption is quite larger in detached houses than in apartments (mostly due to a larger floor area and a larger set of electrical appliances), an adjustment is necessary to simulate consumption in apartments. In [64], which presents the overall energy consumption of 8,230,596 detached houses and 2,059,428 apartments in Canada, the average electricity consumption of an apartment is approximately 57% of the one of a detached house. If one wants to simulate detached house, the 'type of building' sub-factor should be set to 1, but it needs to be 0.57 for apartment units.

3.3 *Comparison of the model with in situ measurements*

The model was compared with measurements taken in a recently constructed multi-residential social housing building in Quebec City, Canada. Data measured in this building include DHW volumetric demand for each of the 40 dwellings along with the electricity consumption of eight apartments. These quantities were measured every 10 minutes. In addition of the real-time measurement of electricity for some of the dwellings, the electricity consumption of the remaining 32 dwellings is recorded every month by electricity meters. Since heat needed for space heating and DHW is provided to the building by hot water from a district heating system, the electricity consumption is entirely used for non-HVAC purposes. The monitoring duration considered for the validation is a full year (from January 1st 2016 to January 1st 2017). This dataset was independent from the tool – it was not used in the making of the model and therefore can be used for independent validation. In practice the occupant behavior model could be used before the construction of the building (e.g., for energy simulations or sizing equipment) and therefore, it would not be possible to fit to adjust the model from in situ measurements.

The total population of the building during the monitoring period is 90 people (an average of 2.25 occupants per household). According to the household size distribution used in the model, this number is lower than average, but not abnormally low (22nd percentile of possible building population). For both DHW and electricity consumption, the objective of the present work is to achieve a model that accurately depicts stochasticity in occupant behavior while still offering satisfying aggregated results. Therefore, the validation of the model is divided in two parts. The first part will check the aggregated patterns, where the whole building consumption is compared to aggregated results from the model. The other part of the validation will study diversity in consumption between individual households. Because no data were taken for active occupancy in the real building, this part of the model cannot be directly validated. However, due to its link with the other two simulated behaviors, adequate consumption representation will indirectly reveal whether the occupancy is appropriately simulated. Furthermore, it has already been shown in Fig. 3.2 that the active occupancy model generates satisfying results regarding aggregated national statistics.

3.3.1 Aggregated demand

Consecutive simulations of the same building can provide different results due to the stochastic nature of the model. To quantify the different possible levels of DHW and electricity consumption of the building, multiple simulations were performed and compared with the monitored building to obtain various overall annual profiles. The number of simulated dwellings was set to 40, the number of days to 365 and the household size distribution is identical to the one found in the real building (i.e. each simulation had a population of 90 people). The evolution of the distribution of building consumption is presented in Table 3.4 as a function of the number of simulations performed. The non-zero standard deviation (which refers to the deviation found from the distribution of average DHW consumption of each building simulation) demonstrates that the total DHW and electricity consumption of the building cannot be precisely known before operation due to the occupant behavior, even if the impact of every household is smoothened over 40 dwellings. After 100 simulations (translating into a total of 4,000 simulated dwellings), the average daily DHW use and electricity demand are respectively 134.8 litres per dwelling and 13.86 kWh per dwelling. A consumption level of 134.8 litres corresponds to a reduction of 40% from the value provided by National Resources Canada in 2012 (225 litres; see Table 3.1) for the average hot water consumption in a Canadian dwelling [67]. This significant drop between the model and the expected value can be explained by the small number of occupants in the building and by the installation of water saving devices. In another recent monitoring study in Canada, an average demand of 172 litres per day was measured over a sample of 119 homes that had a mean household size of 3.83 people [68]. Therefore, it is not aberrant that the level of consumption in the model is lower than the value reported by National Resources Canada. In fact, in the case study building, the average daily consumption of hot water during the monitoring period was 131.2 litres per apartment. In Fig. 3.6a, the distribution of the DHW consumption in the building obtained with the 100 simulated profiles is illustrated. Since the amount of DHW use in the validation data falls into the distribution generated by the model, it appears that the model is in agreement with the case study building for the total amount of hot water use.

Table 3.4. Variability of the DHW consumption and electricity use profiles as a function of the number of profiles generated

Number of profiles generated	Domestic hot water $\left[\frac{L}{day \cdot dwelling}\right]$		Electricity $\left[\frac{kWh}{day \cdot dwelling}\right]$	
	Average	**Standard deviation**	**Average**	**Standard deviation**
1	135.1	-	13.71	-
5	134.4	6.1	14.37	0.80
10	136.0	5.4	14.17	0.66
25	135.5	5.7	13.93	0.67
50	135.2	6.8	13.87	0.62
75	134.6	6.7	13.89	0.57
100	134.9	7.0	13.86	0.54

The distribution of electricity demand computed by the model is also shown (Fig. 3.6b). The average electricity consumption for a dwelling in the monitored building is 14.81 kWh per day. This figure shows that the measured electricity consumption falls within the values given by the model, with a tendency to be closer to high values.

Figure 3.7 compares the simulated mean daily DHW and electricity profiles throughout the year for all dwellings generated in the 100 simulations with the average profiles found in the validation data. The shaded area around the simulation curves provide the variations seen between all simulations – the area is bounded by the 5th and 95th percentiles observed from the 100 aggregated simulated profiles at every hour of the day. Consumption of hot water and electricity during the night is lower in the model than in the measurements, but the model overrates the morning peak from 7AM to 10AM – it is the only period of the day where the measured curve is out of the range generated by the simulations. After 10AM, the aggregated patterns provided by the model closely follow the ones of the case study building. Nonetheless, measured and simulated profiles have identical behaviors: low-consumption in the early hours, followed by an increase in the morning to a level of consumption that is mostly constant until the evening peak happens. The only large difference between simulations and measurements is the morning DHW consumption. Simulations predict a peak with a consumption rate of nearly 12 litres per hour that is not happening in the monitored building. It can be argued that the occupants living in the case study building do not follow a “typical” daily DHW schedule as morning peaks are seen in most DHW monitoring studies [134]. For instance, in the previously mentioned monitoring study made in Canada [68], the consumption of hot water between 6AM and 10AM represents 28.3% of the total daily DHW demand whereas in the building used in this paper, this value goes down to 18.8%. In the simulated profiles produced by the model, 23.5% of the DHW consumption is made in that morning period. A possible explanation to this unusual behavior in the monitored building is that due to a high proportion of children, baths are more often taken in the evening instead of in the morning. Another reason for the differences might be that the modeling of active occupancy is not “perfect”. Since the occupancy in the simulations is based on British schedules, there could be some errors in the representation of Canadian occupancy patterns. For example, the increase of consumption in the morning happening approximately one hour earlier in the validation data versus in the simulations can be due to the fact that Canadians wake up on average an hour earlier than British. Since metered data comes from a social housing building, socioeconomic factors might also explain why the DHW use has no morning peak, but a more balanced consumption during the day. A similar observation can be made for electricity – the simulation results predict more consumption between 7AM to 9AM than what is seen. Again, the metered profile slightly differs from what is seen in other electricity monitoring analyses, with a proportion of 6.1% of electricity being consumed between 7AM to 9AM. Two different samples of houses in Canada (one of 29 households in Nova Scotia and the other of 22 households in Ottawa) have a proportion of approximately 8.0% and 8.3% of electricity consumed during this period of the morning [135]. Larger samples in Europe have also yielded a fraction around 8% [56][57]. The model predicts on average that 8.4% of the electricity is used between 7AM to 9AM. Again, the discrepancy between the building used in this paper and others suggests that socioeconomic factors not only have an impact on total energy demand, but also on the timing of such demand with social housing occupants apparently adapting different schedules. The shape of the measured electricity consumption profile is similar to the one simulated for the weekend (the models predicts that to 7AM to 9AM period is responsible for 6.7% of electricity use during the weekend).

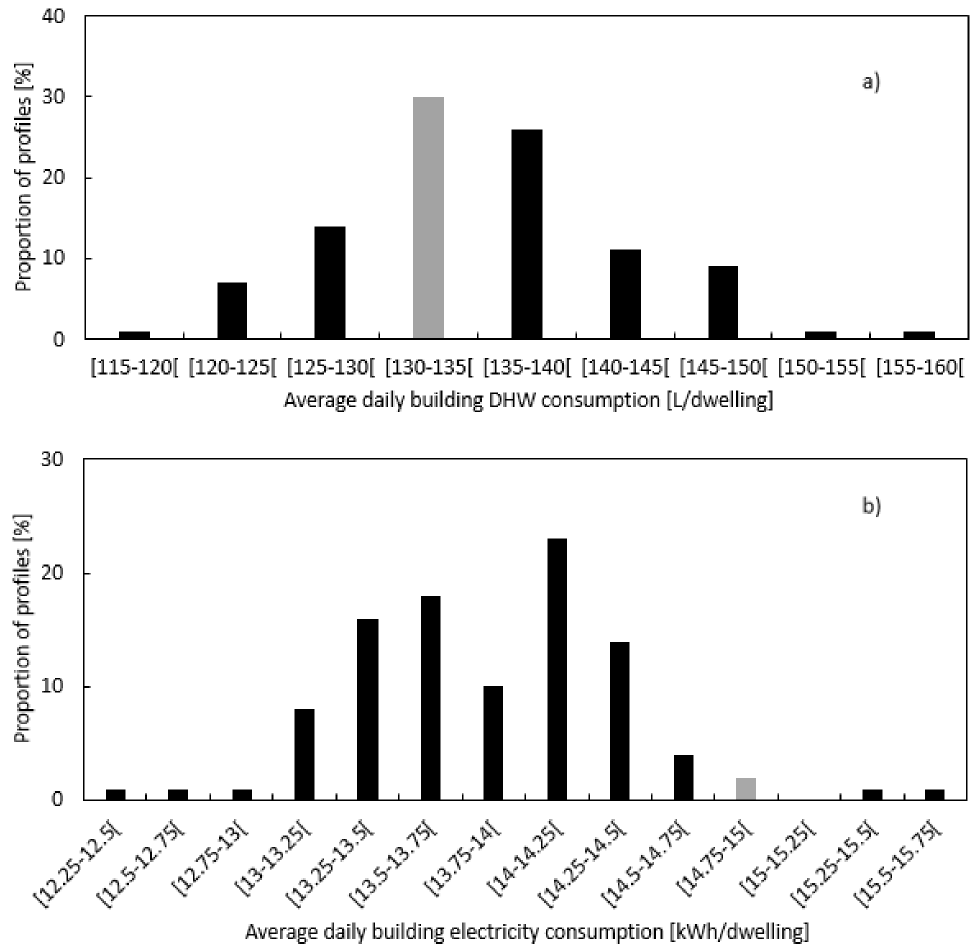


Figure 3.6. Distribution of the a) average DHW and b) electricity daily consumption per dwelling obtained after 100 simulations. Shaded bar represents the cluster in which the monitored building falls into.

Notwithstanding this difference in the morning, peak heights are roughly the same in the simulated and measured datasets. Regression coefficients between the measured and generated time series are $R^2 = 0.855$ for DHW and $R^2 = 0.890$ for electricity consumption. Moreover, the differences seen between the measured and simulated DHW use profiles do not lead to errors for the sizing of the hot water system (see Chapter 5). It can thus be concluded that the aggregated daily behavior of the model fits reasonably well with the measurements and that one to improve the model. If the goal was to represent more closely the case study building, one would need to scale down the probability of DHW and electricity demand events in the morning.

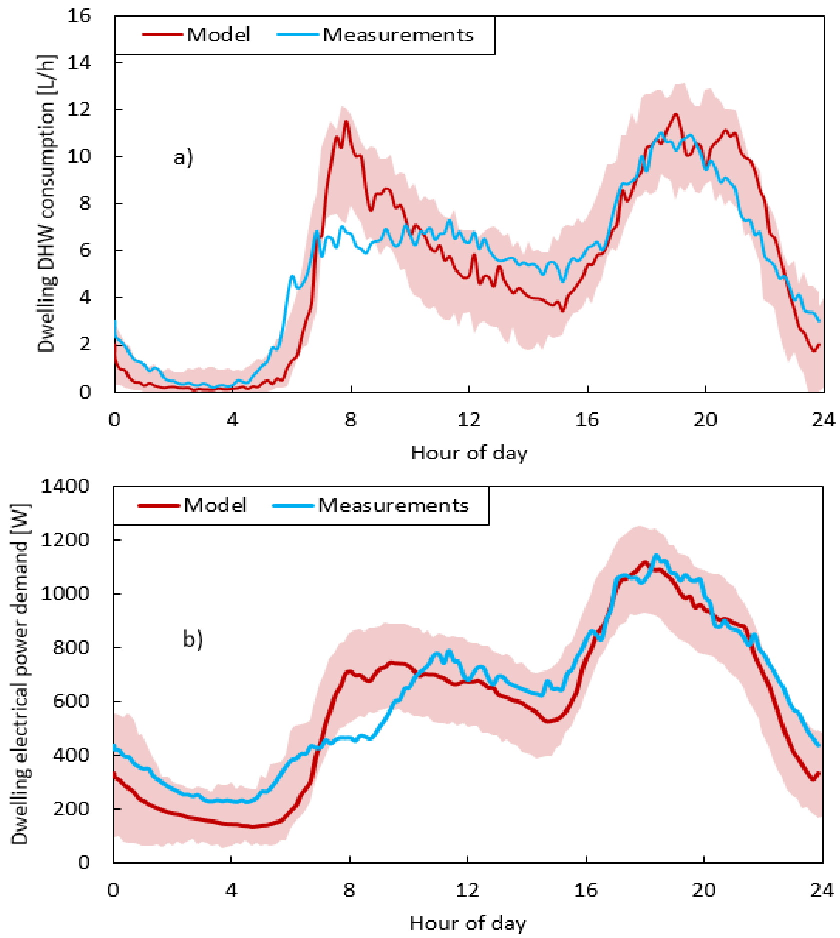


Figure 3.7. Daily a) DHW and b) electricity use by simulated and measured dwellings over a year from one simulation. Shaded areas represent the range prescribed by the 5th and 95th percentiles obtained from the 100 simulated profiles. a) DHW and b) electricity profiles from 100 simulations compared to the one measured from the case study building.

3.3.2 Disaggregated demand

The variability in consumption between different dwellings generated by the model is examined in contrast with the one observed in the real building. Among the 100 simulated building profiles, the one that produced the level of DHW consumption and electricity that were the closest to the real building was selected and is analyzed here. The measured standard deviation of daily consumption between the 40 dwellings is 95.2 litres for hot water and 5.93 kWh for electricity. In the selected simulated profiles, these values respectively are 42.5 litres and 6.60 kWh, meaning that although the variability for electricity consumption is accurate, the model is conservative in terms of variability among households for domestic hot water. Further work to obtain more data about this variability would be helpful to get an improved representation. The goodness-of-fit between the observed distribution and the one predicted by the model was assessed with Mann-Whitney test. The computed p-values are $3.52 \cdot 10^{-5}$ for the hot water distribution and 0.357 for electricity use. At a significance level of 95%, these values mean that the model fits with observed data for electricity consumption, but not for DHW. This is confirmed by Fig. 3.8 which displays separately the consumption of every measured and simulated dwelling. In the case of DHW (Fig. 3.8a), contrarily to the simulation results, there are several very-heavy users in the building as well as low-consumption occupants.

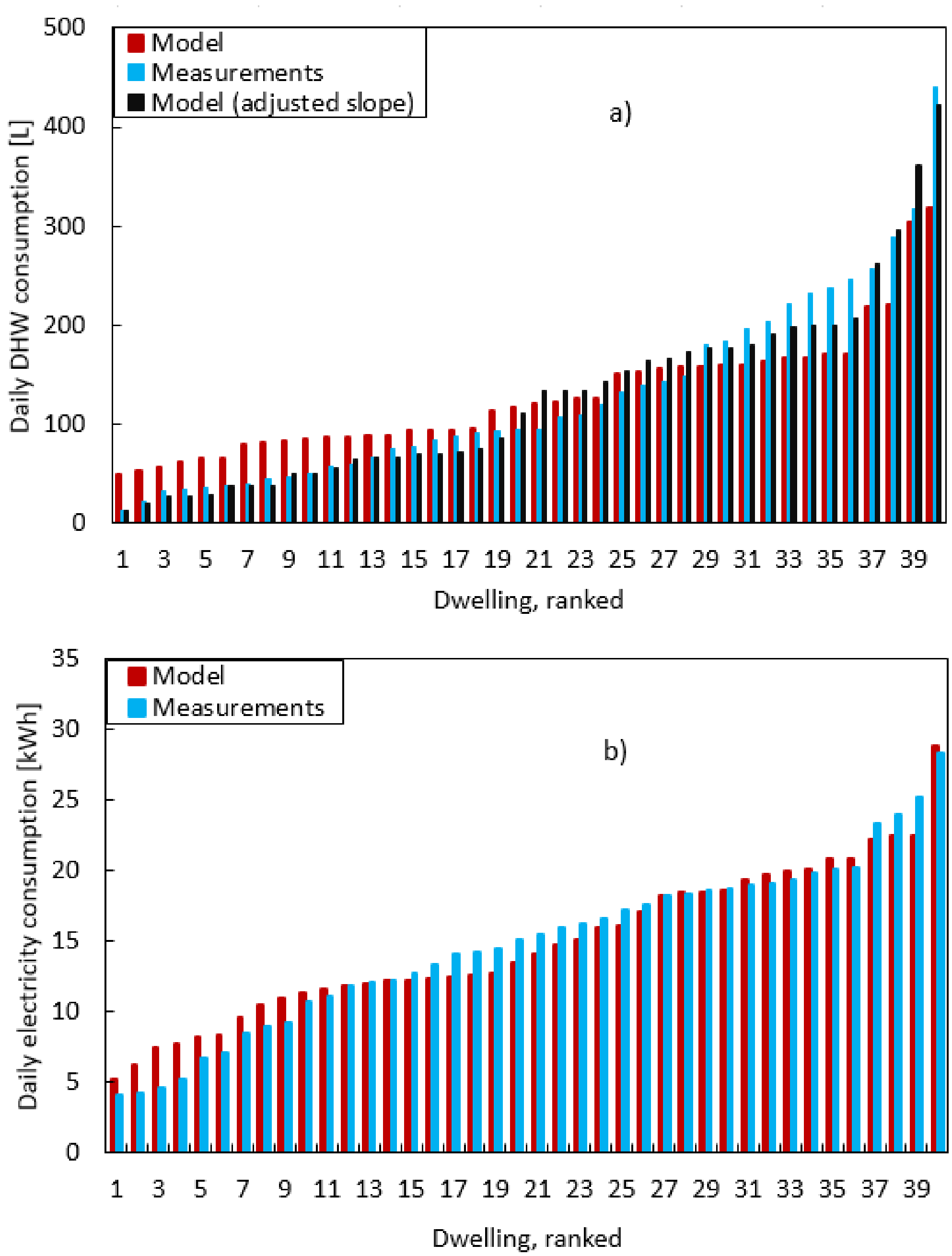
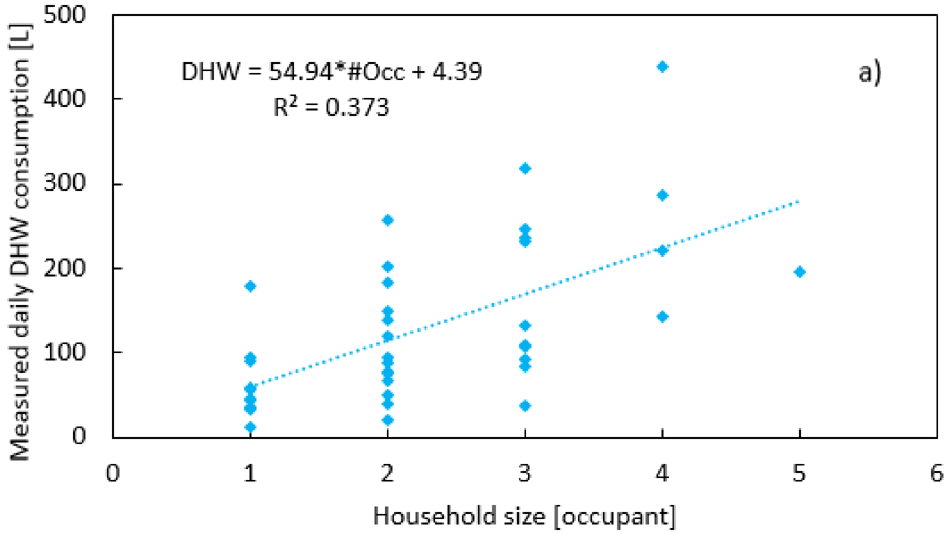


Figure 3.8. Average daily a) DHW and b) electricity profiles from 100 simulations compared to the one measured from the case study building.

To identify the reason behind this disparity, the DHW consumption of dwellings was plotted in Fig. 3.9 by separating them according to their household sizes. Fig. 3.9 also offers best fit lines computed from linear regression for the estimation of DHW demand with the household size. The diversity of consumption around the linear regressions is slightly underestimated by the model. The larger diversity in the measured data appears to be mostly caused by the larger impact of household size on hot water use. A comparison of the linear regression equation reveals that the household size has twice as big an influence in the monitored data (slope of 55 litres per person) than in the simulations (27 litres per person). Consequently, there is an important difference in consumption between dwellings with low and high household sizes, explaining the larger variability. The test was re-run with a slope of 55 litres per person prescribed in the model. This modification significantly increased the goodness-of-fit between the distribution seen in the monitored building and the one predicted by the model. The new p-value of 0.331, indicating that both distributions fit at a significance level of 95%. Black bars in Fig 4.8a represent the interhousehold distribution obtained with the new slope – it can be seen that it follows the measured distribution more closely than the simulated distribution generated with the previous slope. A slope of 55 litres per occupant is larger than those found elsewhere. Studies have reported a slope of 26 L/person in the UK [134] and of 35 [122] and 39 L/person [68] in surveys made in Canada. The presence of numerous families with young children might once again be responsible for this difference. Larger households are those with young children, who consume more hot water, hence the increase of the slope. The slope used in the model can easily be readjusted by users.



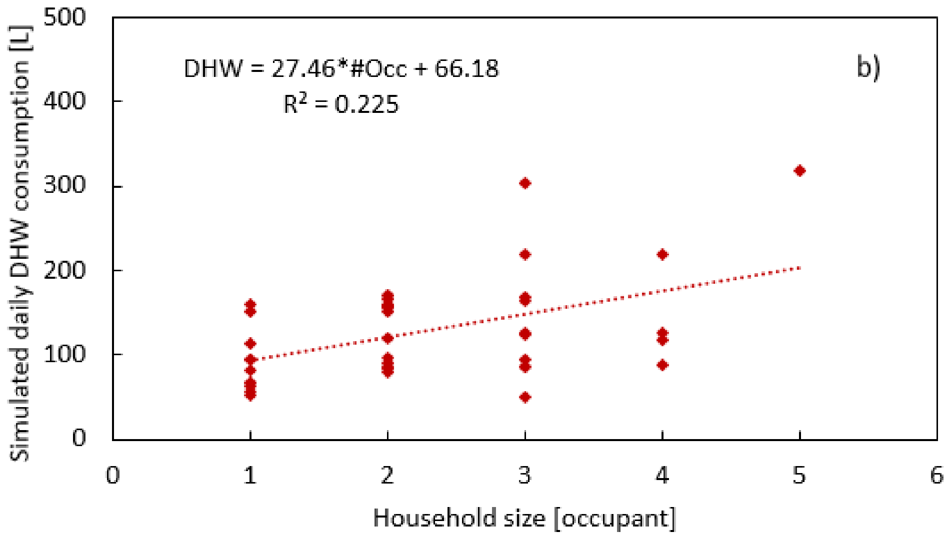


Figure 3.9. Consumption of DHW as a function of household size according to a) measurements and b) simulations.

Fig. 3.10a offers a visual depiction of how all simulated DHW consumption profiles fared when compared with measured data. The first column on the left that is separated from the others is the measured profile, from the lowest-consuming dwelling to the highest. The other columns represent the 100 profiles generated from simulation, after the change the DHW-per-occupant slope. Note that for the sake of visibility, the colorbar is topped at 300 L per day. Fig. 3.10b presents the inverse cumulative distribution function of daily DHW demand from metered data (blue curve) and simulations (shaded areas). The black shaded area is the variations seen from the 5th and 95th percentiles observed from the 100 simulated profiles before the change of the slope and the red one is obtained after the change, showing that the change of slope was beneficial. When expressed on a per capita basis, simulated daily DHW consumption vary from ~31 L per day per person to ~114 L per day per person, from low-use to high-use consumers. This result is coherent with literature, e.g. ASHRAE handbook [69].

Figs. 3.10c and 3.10d are respectively the electricity consumption equivalent of Figs. 3.10a and 3.10b. Again, a maximum value of 30 kWh is used in Fig. 3.10c to improve visibility of the variations. Fig. 3.10d reveals that the 100 simulated profiles all match fairly well with the measured building profile, except for a slight divergence for the low-consuming households (those set in the lowest 10%).

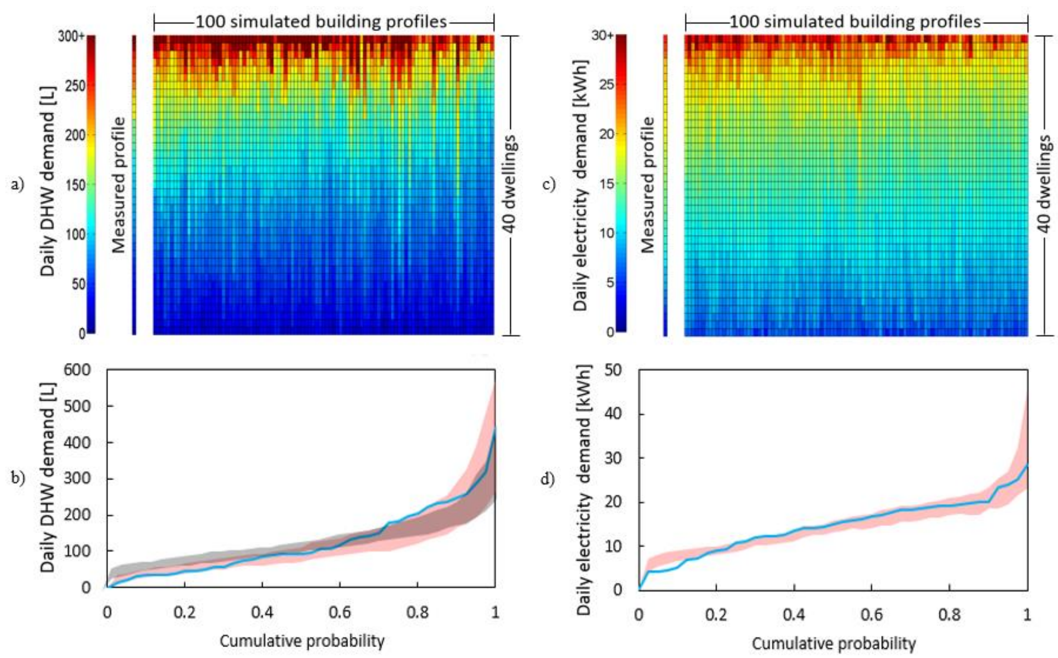


Figure 3.10. a) Average dwelling daily DHW consumption for all measured and simulated profiles (x-axis: the 100 profiles, y-axis: the 40 dwellings). b) Inverse cumulative probability function of the DHW consumption of a dwelling from measurements and simulations. c) Average dwelling daily electricity consumption for all measured and simulated profiles (x-axis: the 100 profiles, y-axis: the 40 dwellings). d) Inverse cumulative probability function of the DHW consumption of a dwelling from measurements and simulations.

Mann-Whitney goodness-of-fit tests yields acceptable fit at a significance level of 95% for 97 of the 100 slope-adjusted DHW profiles (from 3 out of 100 with an unadjusted slope) and 92 of the 100 electricity profiles.

Stochasticity not only requires diversity in consumption between different dwellings, it also asks for variability between every day for a single dwelling. People do not consume the same quantity of energy day after day. Figs. 3.11 and 3.12 exhibit the day-to-day variability of the measured and simulated dwellings. Centerlines in the boxes represent the median day of consumption, edges of the boxes the first and third quartiles and the whiskers show the position of the 5th and 95th percentiles. Note that for electricity, Fig. 3.12 could only be generated for the eight dwellings whose electricity consumption is measured as daily consumption for the other apartments is unavailable. For both DHW and electricity, the model generated day-to-day variability that is nearly constant for all dwellings as shown by the similar length of the boxes and whiskers in Figs. 3.11b and 3.12b. A different pattern is seen for the measured data, in which day-to-day variability is high different between dwellings. Some households consume a very consistent volume of DHW day after day and others do not. For example, in the case of electricity demand, dwellings #3 and #4 have a nearly identical median day, but the narrower box evidences that the consumption in dwelling #3 is much more consistent than in dwelling #4.

The average day-to-day standard deviation for DHW is 65.9 litres in the validation data and 57.9 litres in the simulation profile. For electricity, these values are 6.13 and 4.48 kWh respectively, so it appears that the day-to-day variability is underrated. No factor was introduced in the model to force diversity of consumption between different days for a single dwelling. This diversity is driven by the stochastic nature of the occupant behavior model. It appears that this is not sufficient and that another factor would be valuable to enhance the day-to-day variability of a simulated dwelling. Such factor could be drawn from a PDF and could vary every day.

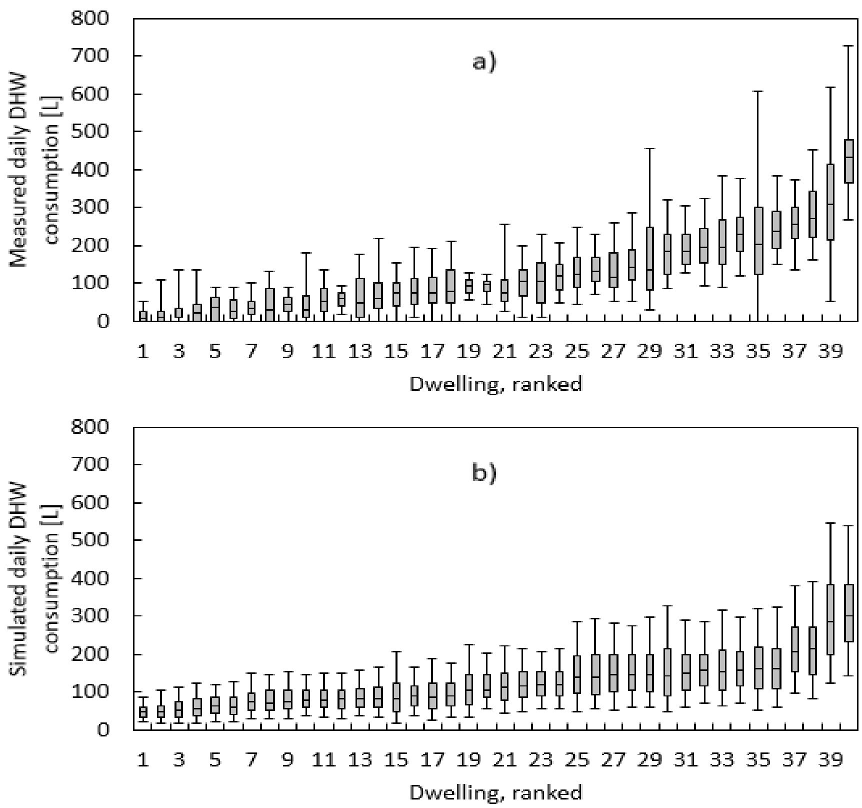


Figure 3.11. a) Measured and b) simulated day-to-day variability of DHW consumption.

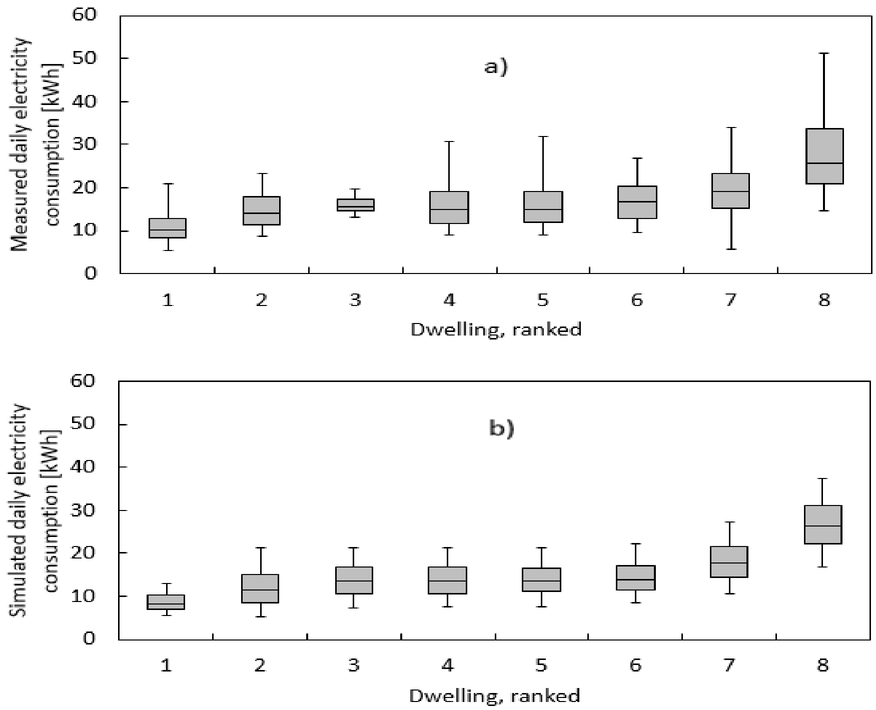


Figure 3.12. a) Measured and b) simulated day-to-day variability of electricity consumption.

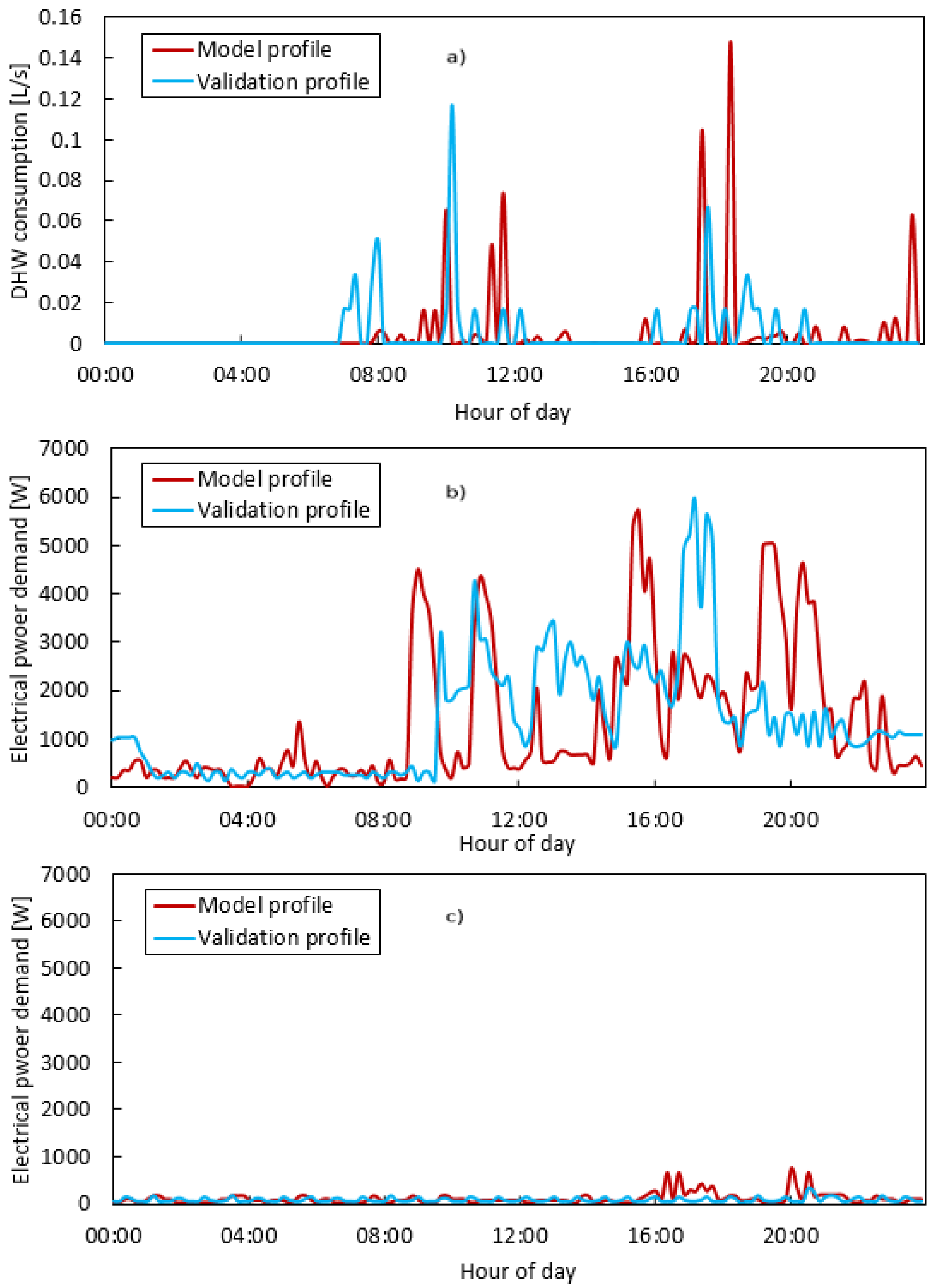


Figure 3.13. Simulated and measured daily schedule of a) DWH use during the highest day of consumption b) electricity use during the highest day of consumption and c) electricity us during the lowest day of consumption for a selected dwelling.

Figure 3.13 illustrates the consumption schedules during individual days for one selected dwelling. The dwelling was randomly selected from the simulation profiles and then it was paired with a dwelling from the monitored building that yielded a similar level of consumption. Fig. 3.13a presents the maximum day of DHW consumption (a total volume of 370.0 litres was consumed during that day in measurements, 399.3 in simulations), Fig. 3.13b the maximum day for electricity consumption (32.3 kWh in measurements, 32.4 in simulations) and Fig. 3.13c the minimum day for electricity consumption (2.2 kWh in measurements, 3.0 in simulations). The day that had the lowest use of DHW is not displayed since in both the model and validation datasets this day had zero consumption of hot water. The purpose of Fig. 3.13 is merely to show the profile trends – a perfect match between the curves is not expected. The DHW curves have a similar behavior: zero consumption for most of the days along with ten to twenty spontaneous short consumption events. Peaks of consumption related to an occurring event have comparable magnitude. The peak heights are also similar for electricity consumption. Curves for this part of the model show that electricity use oscillates when the dwelling is in "standby mode". When occupants are truly using electrical appliances, the power demand increases greatly. A zoom on Fig. 3.13c exposes that the standby power is smaller in the model (41 W) than it was in the monitored dwelling (60 W). This gives a reason for the underestimation of consumption during the night in the aggregated profile (see Fig. 3.7). Nevertheless, extreme days yield similar total amount of energy use between the simulated and the measured apartment. The overall trends were adequately reproduced, demonstrating the capacity of the model to generate realistic daily profiles.

Overall, there is a good fit in terms of aggregated and disaggregated patterns between the profiles that are generated by the model and the measurements made in a real building. Yet, there remains discrepancies that suggest that more data has to be collected for further improving the model. For example, a 'day-to-day variability' factor which control the consumption level of every day could be useful for the tool, but no study on the day-to-day variability in consumption can be found in literature and thus it is not possible to obtain an appropriate PDF from which this factor could be drawn. Additionally, one could question the relevance of adding such a factor as it would slow down the computations without necessary adding information that is important for building design. Another way of improving the tool could be the characterisation of different user types via a differentiation of behavior. The model could assign to each dwelling the type of DHW users (morning versus evening users) that live in it and then adjust hot water events PDFs accordingly. To do so, one needs to know the proportion of people that consume more water in the morning, which is very difficult to quantify.

3.3.3 Effects of changes on the tool performance

To create a unified stochastic tool for the simulation of occupant behavior in residential buildings, several changes were applied to already existing models as described before. This section verifies how each of these changes influences the accuracy of the simulations. Three indicators were chosen to assess the performance of the occupant behavior model. First, the relative difference of overall consumption between the case study building and the average obtained from 100 simulations of the building was computed:

$$I_{cons} = \frac{\frac{1}{n}\sum_{i=1}^{n} Q_i - Q_m}{Q_m} \times 100\% \tag{4.7}$$

where Q_m is the average daily measured quantity, Q_i is the average daily simulated quantity for the ith generated profile and n is the number of simulated building profiles (n = 100 here). The second performance indicator is related to the timings of consumption and looks at the average daily schedule of consumption:

$$I_{sched} = 100\% \times \frac{Q_m}{\bar{q}_m} \sqrt{\frac{\sum_{j=1}^{144} \left(\frac{q_{j,m}}{Q_m} - \frac{1}{n}\sum_{i=1}^{n} \frac{q_{ij}}{Q_i} \right)}{144 - 1}} \tag{4.8}$$

where $q_{j,m}$ is the average measured rate of consumption for the j^{th} time step of the day and q_{ij} the average simulated rate of consumption obtained from the i^{th} generated profile. The 144 value in Eq. (4.8) comes from the fact that there are 144 time steps during a day when using a 10-min frequency. The average rate of consumption are divided by the average daily consumption in order to ensure that changes in overall consumption (which are already measured by the first indicator) do not also influence the second performance index. The final indicator is the discrepancy between the measured and simulated coefficient of dwelling-to-dwelling variation:

$$I_{dwellings} = \frac{\frac{1}{n}\sum_{i=1}^{n} CV_i - CV_m}{CV_m} \times 100\% \tag{4.9}$$

The coefficient of dwelling-to-dwelling variation is defined as the standard deviation of the overall consumption of dwellings in a building divided by the average consumption of the building. Once again, dividing the standard deviation by the average consumption ensures that discrepancy in overall consumption will not be reflected in this indicator. The three performance indices were computed after each change was cumulatively applied to the occupant behavior tool for both DHW and electricity consumption. The computed indices are presented in Table 3..5. The blue cases in 4.5 were implemented before this validation test to represent where changes are expected to have an effect on the model, e.g. the first change (scaling for apartment or detached houses) is only expected to influence the overall consumption of electricity predicted by the model.

All three indicators are error functions, so low values for the indicators indicate better performance. The figures in Table 3.5 demonstrate that the changes applied were greatly beneficial for the prediction of DHW and electricity use in terms of overall consumption in the building and of dwelling-to-dwelling variability. For the DHW section, adjusting the daily hot water use from 27 to 55 L per occupant as done during the validation reduced the underestimation of dwelling-to-dwelling variability from 37.2 to 9.4%. Although an underestimation of 37.2% as initially obtained after applying the "type of consumer" parameter appears unsatisfactory, the introduced parameter still significantly reduced the error on the dwelling-to-dwelling variability as it was set at an underestimation of 83.9% in the original model. The introduced modifications did not have a high impact on the timings of the hot water consumption, merely reducing I_{sched} from 30.4 to 24.2% for DHW and from 18.6 to 15.1% for electricity. This is explained by the fact that the changes brought to the occupancy part of the model had no significant impacts on the simulation, with the three performance indices staying nearly unchanged before and after the introduction of those changes. It appears that the two scale factors related to occupancy were not able to correct the fact the schedules obtained from British lifestyle was used to simulate the behavior of Canadians. The fact that social housing building was used for the validation can also explain this lack of improvement as occupancy behavior in a dwelling can change according the socioeconomical status of its occupants. More data on active occupancy and activity schedule need to be available if one wants to improve the prediction of the scheduling of hot water and electricity events in the occupant behavior model.

Table 3.5. Performance of DHW and electricity prediction after applying various changes applied to already existing occupant behavior models.

#	Section of the model	Change	DHW			Electricity		
			I_{cons} [%]	I_{sched} [%]	$I_{dwellings}$ [%]	I_{cons} [%]	I_{sched} [%]	$I_{dwellings}$ [%]
0		-	72.5	30.4	-83.9	-41.4	18.6	-73.6
1	Electricity	Scale for type of dwelling	72.6	30.6	-83.7	-66.6	18.5	-74.7
2		Scale for electricity appliances (UK to Canada)	72.5	30.6	-83.9	-14.4	15.5	-74.7
3		Scale for occupant activities (UK to Canada)	72.4	30.5	-83.8	-7.6	16.7	-72.4
4		Electricity/Household size slope	72.6	30.7	-83.8	-8.4	16.8	-26.1
5		Add the "Type of consumer" parameter	72.4	30.6	-83.8	-8.4	16.8	-7.1
6	DHW	Link DHW with occupancy	24.1	24.4	-92.1	-7.9	16.8	-6.7
7		Scale for hot water appliances (USA to Canada)	22.4	23.9	-92.3	-8.9	16.8	-7.4
8		Scale for low-flow devices	3.2	23.6	-92.7	-8.3	16.8	-6.8
9		Add the "Type of consumer" parameter	2.9	23.5	-37.2	-7.8	16.8	-7.9
10		Adjusted the slope from 27 to 55 L/(day*person)	2.6	23.4	-9.4	-8.2	16.8	-7.3
11	Occupancy	Scale for active occupancy (UK to Canada)	2.2	23.9	-9.1	-5.9	15.6	-5.2
12		Add the "Type of occupant" parameter	2.7	24.2	-9.5	-6.4	15.1	-2.0

3.4 *Conclusions*

A strategy to create a unified non-adaptive probabilistic occupant behavior model for Canadian multi-residential buildings was proposed and tested. This strategy merges multiple recognized models built in different part of the world. Since occupants in different countries could have different behaviors, scaling is necessary to adapt already existing models to specific locations worldwide. This was possible since Canada, US and UK share similar occupant behavior patterns. Modifications were also necessary to make sure that the outputs from the occupant behaviors models were coherent. In this paper, this idea has been shown to be possible for Canadian lifestyle. The scaling was based on national aggregated statistics about the time use, the DHW demand and electricity consumption of Canadians. These data are more accessible in most countries than the large datasets required to build a new occupant behavior model. Therefore, it appears easier to scale a model from a country to another than to completely create a new model. The behaviors considered in the developed model are occupancy, domestic hot water use and consumption of electricity. The model has a time resolution of 10 minutes. Four already existing tools were merged and scaled in this new model: Richardson's active occupancy and domestic electricity use models, Hendron's DHW profile generator and Armstrong's model for the simulation of stochastic lighting loads in dwellings. It was found that it was also needed to use additional scale factors to ensure that there is a significant diversity in consumption between different dwellings and that the level of consumption is coherent with the household size of the dwellings.

The outputs of the model were validated with a multi-residential building in Canada. The validation section of this work shows that the aggregated simulation and measurement results are in agreement only with small discrepancies that could be explained by a lack of data. The total consumption of the building falls into the range predicted by the model and in spite of minor differences, the average daily profiles have similar patterns. Most of the differences between the model and measurements might be explained by the large number of young families in the real building due to its social housing vocation, which is atypical given that one usually finds a good mix of household types in typical developments. The diversity of consumption between the dwellings is well replicated for electricity but not for DHW, which is underestimated. Further analyses have shown that this underestimation is mainly caused by the misrepresentation of the relation between DHW consumption and household sizes. Household size is more important for DHW demand than usual in the monitored building, again likely due to the numerous young families. As for the day-to-day diversity of consumption for an apartment, while its representation was adequate for DHW consumption, the diversity for electricity demand is too narrow when compared with validation data. An additional scale factor that infers different levels of consumption for each day could fix this shortcoming. New studies on the variations of electricity consumption between different days for one household would be necessary to implement such a factor and is recommended for further work. Nevertheless, the newly developed tool was shown to offer better performance than the original models for the simulation of DHW and electricity consumption in a multi-residential building in Canada.

The model was developed with the objective of being coupled with building simulation software. The model could also be used in several disciplines such as sociology, psychology, grid design, urban logistics and many others. With respect to energy assessment tools, the generated profiles could directly provide occupancy, DHW and electricity use time series to the building numerical model, which is crucial for the calculations of internal gains and of the overall energy demand of the building. To estimate internal gains generated by the occupants themselves or for performing calculations of air quality and contaminants diffusion, it would be beneficial to know when they are sleeping in the building. The model currently does not discern between being away from the building and being in the building, but sleeping. Therefore, a possible improvement would of a third state (sleeping) in the occupancy model. Also, socioeconomic factors were not directly considered in the version of the tool presented in this paper. In preconstruction simulations, it could be difficult to know the household composition of a dwelling. Instead of weighting the tool for age, gender, salary and other social parameters, it was thus decided to use scale factors drawn from probability density functions created to simulate the variability in consumption related to those parameters. Although it would require significantly more data, considering socioeconomic factors (age, salary, energy price, education…) could increase the accuracy of the model, in particular when one wants to simulate a specific and existing building for which this information is available. It was found for instance that a young population and/or occupants of social housing buildings can lead to a more balanced energy consumption rates during the day with no peak of consumption during the morning.

The existing base models used to create the united tool presented in this paper were developed in Canada, United Kingdom and United States. Although differences in occupant behavior are observed between these countries, one could argue that their culture and socioeconomical environment are similar, which eased the process to adapt the models for Canada. The methodology would need to be tested with countries that have a vastly different culture. To minimize cultural bias in the scheduling of occupancy and of energy events, using occupancy data or models from a specific country will always be preferable than using scaled data from another country, but when this option is unavailable, the scale strategy seems to provide satisfying results for the generation of realistic energy use profiles.

CHAPITRE 4. SIZING METHODOLOGY FOR DOMESTIC HOT WATER SYSTEMS BASED ON SIMULATED OCCUPANT BEHAVIOR

Résumé

Dans une perspective de transition énergétique, l'énergie nécessaire pour octroyer de l'eau chaude domestique aux occupants de bâtiments résidentiels est de plus en plus étudiée. La conception de systèmes d'eau chaude devient ainsi très importante. Le dimensionnement de tels systèmes est habituellement basé sur certaines règles du pouce pour évaluer la demande en eau chaude d'un bâtiment. Une mauvaise évaluation de cette demande peut mener à un système de mauvaises dimensions. Cela se traduit soit par une quantité insuffisante d'eau chaude à offrir aux occupants ou en un système surdimensionné qui n'est jamais utilisé à ses conditions optimales. Bref, il est important d'évaluer avec justesse la demande en eau chaude de bâtiments résidentiels lorsqu'on conçoit leur système d'eau chaude. Pour aider les ingénieurs à ce sujet, un outil stochastique basé sur des modèles disponibles dans la littérature a été conçu pour générer des profils de demande en eau chaude. Cet outil a été validé en utilisant des données réelles provenant d'un bâtiment résidentiel situé à Québec. Ce bâtiment contient 40 appartements dont la demande en eau chaude était enregistrée. Une nouvelle méthode de dimensionnement des systèmes d'eau chaude basé sur cet outil de génération de profils d'eau chaude domestique est proposée dans cet article. Les résultats obtenus avec cette méthode sont comparés avec ceux provenant de la démarche traditionnellement utilisée.

Abstract

As households are being more energy aware over the years, the energy consumption for providing domestic hot water (DHW) is receiving increasing attention. Thus, the design of hot water systems is becoming more important to ensure a holistic approach to energy reduction. Current sizing for these systems is often based on empirical practice. An inaccurate evaluation of the hot water demand could lead to a poor hot water system design. This either means an insufficient amount of hot water available to occupants or an oversized system that never gets to be used under its optimal operational point. Therefore, it is crucial to properly evaluate the hot water demand when designing hot water systems for dwellings. As an attempt to help engineers in the design process, a stochastic tool was constructed based on validated published tools to generate hot water demand profiles for residential buildings. This novel tool has been validated using real data from an apartment building in Quebec City, Canada. This building includes 40 apartments where hot water demand was monitored. A comparison between the monitored and simulated hot water demands of the building shows great accuracy of the tool. An improved sizing method based on the DHW profile generation tool is proposed and compared to traditional sizing methods.

4.1 *Introduction*

Monitoring studies carried out in the past have shown that occupant behavior produces large disparities of energy consumption between similar buildings [24]. Therefore, an erroneous representation of the occupant behavior during the design phase can lead to inappropriate HVAC&R designs. This is especially true for DHW where an inaccurate evaluation of the hot water demand could lead to a hot water system design that is either undersized or oversized. This either means an insufficient amount of hot water available to occupants or an oversized system that never gets to be used at its optimal operational point. For that reason, it is crucial to properly evaluate the hot water demand when designing hot water systems for dwellings. Usually, deterministic reference load profiles are used to represent DHW demand. These profiles do not account for diversity in multiresidential buildings nor for the day-to-day variations of consumption, which makes it difficult to identify peak demand, an essential parameter for sizing water heating systems. In order to help engineers in the design process of DHW systems, a stochastic tool was constructed to generate DHW use profiles for residential buildings. This tool has been validated using real data from an apartment building in Quebec City, Canada. This building includes 40 apartments, which water consumption of which was monitored.

The purpose of this study is to investigate the possibility of improving the sizing procedure of water heating systems of residential buildings by increasing the accuracy of the representation of the occupants' behavior. Therefore, this paper describes the developed DHW profile generator and then introduces a methodology to design DHW systems, based on annual demand profiles. The monitored building is also used as a case study with a comparison between the building water heating system design and the one obtained with the proposed methodology.

4.2 *Case study building*

The reference building is a monitored multi-residential (social housing) building built in 2015 in Quebec City, Canada. The DHW consumption of each of the 40 dwelling units contained in the building was measured every 10 minutes. The ongoing measurement campaign started on October 2015. The building was constructed with the objective of limiting energy consumption. Therefore, water saving devices were installed in the showers and the sinks.

However, no special training was offered to the tenants regarding the energy performance of their apartments. The hot water system uses four vertical storage tanks that have a volume capacity of 450 L (119 gal) each, resulting in a total storage volume of 1,800 L (476 gal). A district heating hot water loop provides the required heat for the DHW production, via a heat exchanger. DHW is stored in the tanks at 60°C (140 F). The nominal flowrate on both sides of the heat exchanger is 1.93 L/s (30.55 GPM). Considering the effectiveness of the heat exchanger and the two input temperatures, this translates to a heat capacity of 300 kW (1024 kBTU/h) for the hot water system.

4.3 *Current ASHRAE recommendations*

According to ASRHAE guidelines for the sizing of hot water systems in apartment buildings [69], the first step to follow for the design of hot water systems is to estimate the amount of water used during the consumption peak. A table in the above-mentioned handbook contains the necessary information for this evaluation by providing the per capita DHW demand for apartment buildings during the highest peak of the year. The data used to built this table were obtained from studies made in the 90s [138]–[141]. It provides guidelines for low, medium and high DHW consumption occupants. The designer also chooses the duration of the peak considered (between 5 to 180 minutes). A short peak asks for a high heat capacity since the rate of consumption is increased, but a smaller storage tank is needed since the overall volume of DHW used during the peak is decreased. After making a choice for the two variables, the designer reads from the table the volume of DHW demand per person during the peak. Multiplying this ratio by the projected number of tenants gives the total peak DHW volume V_{peak}. From this value, the adequate values for the heat capacity of the water heating system q_{max} and the volume of the storage tank V_{tank} can be directly calculated:

$$q_{max} = \frac{V_{peak}}{\Delta t_{peak}} \rho c_p \left(T_h - T_c\right) \tag{5.1}$$

$$V_{tank} = \frac{V_{peak}}{0.7} \tag{5.2}$$

The peak volume is divided by 0.7 in the calculation of the storage tank volume because the tank is assumed to contain approximately 70% of hot water (the remaining 30% being already degraded by the arrival of the city cold water). In order to obtain references curves for the case study building, the authors applied this design methodology with an assumed population of 112 occupants (the value used by engineers during their pre-design calculations of the building loads). The resulting curves are shown in Fig. 4.1 with a cross marking the actual design in the case study building. A high consumption load was anticipated for the building, which is normal as ASHRAE recommendations describe social housing occupants as heavy DHW consumers [69]. Some limitations of this method can be noted. In particular, the data used to support the sizing procedure being more than 20 years old, it might fail to provide an accurate prediction of today's DHW consumption due to changes that occurred over that timeframe. For example, low-flow devices are becoming more widespread and the occupant behaviors have evolved with growing environmental concerns. In their 2015 monitoring studies on Canadian dwellings, George et al. measured an average daily DHW use that is 21% smaller than the one proposed by the Canadian software HOT2000 which is also based on older studies [68]. Another limitation of the methodology outlined above is that an arbitrary assumption must be made on the proportion of hot water found in the tank. This assumption has a great influence on the resulting design, hence the need for a way to portray DHW demand with more details.

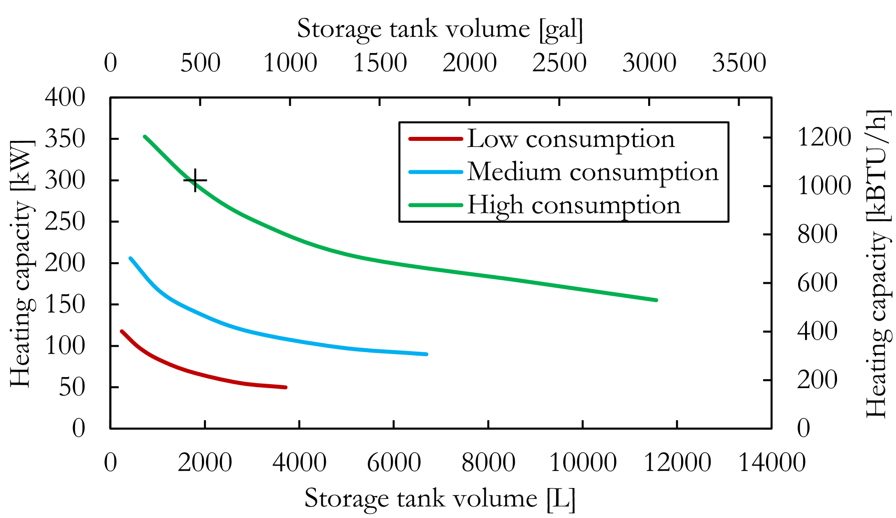


Figure 4.1. ASHRAE guidelines and actual design (black cross) for the hot water system of the building.

4.4 *Occupant behavior tool*

Various DHW use models that generate consumption profiles are found in the literature. One of them is the tool developed by Hendron et al. which predicts the volume of water used by a household based on US data [100]. It divides hot water consumption into five major end-use categories: shower, bath, clothes washers, dishwashers, and sink. Each of these five appliances has a specific daily probability distribution function (pdf) that is used by the model to anticipate hot water events. When such an event is predicted to happen, another pdf (different for each appliance) calculates the volume of hot water used during this event. By applying calibration scalars to account for the type of day (weekday/weekend) and the month of the year, the simulation of 365 days is possible to obtain an annual DHW profile for a specific building.

The authors of this paper added modifications to Hendron's model to improve its applicability. Since the DHW tool uses American data, it might be unable to accurately reproduce the behavior of occupants in other countries. In fact, Americans consume on average approximately 15% more hot water than Canadians [67], [124]. Therefore, to make sure that Hendron's model is applicable for the case study building, aggregated statistics on the use of DHW for showers, baths, sinks, dishwashers and washing machines by Canadians were used to scale the Hendron's tool for Canadians lifestyle [67]. Another shortcoming of Hendron's tool is the lack of consideration for occupancy in the simulated building. It is important to account for occupancy when forecasting DHW use, as the number of events related to DHW use is expected to be proportional to the number of people present in the building at a given time. For this reason, Richardson's active occupancy model, which stochastically projects the number of active occupants in a dwelling, was added to the DHW tool to get the occupancy profile of the building [99]. The latter tool uses probabilities calculated from extensive Time-Use Surveys made in the United Kingdom. Simlarly to the scaling made to the first tool, Richardson's model was adjusted to account for the fact that Canadians spend on aggregate 492 minutes of active occupancy at home versus 527 minutes for the average British citizen [107], [112]. The newly developed tool uses a time step of 10 minutes and only needs two inputs: the number of simulated dwellings and the number of days simulated. It combines the two occupant behavior models by following these steps:

1. Assign a value for the number of people living in each dwelling using a probability distribution established from Canadian household statistics [108].
2. Use Richardson's tool to generate the active occupancy profiles for the specified number of days.
3. Load the daily event probability distribution functions for the hot-water appliances from Hendron's model.
4. Apply to these functions a calibration scalar that accounts for the type of day (weekday/weekend), month, household size and type of DHW consumer. The latter is found from another pdf that has been developed from results of different DHW studies [68].
5. For every simulated day, during time steps where there is zero occupant in the dwelling, modify the pdfs to stop DHW consumption for showers, baths and sinks. Then, apply a new calibration scalar to the pdfs that ensure that the aggregated daily DHW volume is unaffected by this modification.
6. Simulate the specified number of days to projects every DHW event starting time.
7. Everytime a hot water use event is predicted, the event volume of DHW is also predicted. If low-flow devices are installed in the building, then these volume pdfs are reduced by 20% [68].

Thus, for every time step and dwelling, the outputs of the model are the number of occupants and the volume of DHW being used in that time step. The tool was used to simulate one year of operation of the case study building. Fig. 4.2 provides a comparison between the measured and simulated aggregated daily profiles of hot water use (i.e. an average over the different days of the year of DHW consumption at a given time). Although a significant discrepancy is found in the morning (around 8:00), the simulated and measured profiles follow the same patterns for the rest of the day, especially in the evening. More important is the fact that the height of the peaks, which is essential to know for water heating system design, is nearly the same in the measurements and the simulations.

Two consecutive simulations of the same building can provide different results due to the stochastic nature of the model. To assess the change in consumption between different simulations, the simulation of the case study building was replicated 100 times and the results are shown in Table 4.1. After 100 simulations, the average daily consumption of the profiles was 135.0 L (35.5 gal) per dwelling with a standard deviation of 6.8 L (1.8 gal) between the different simulations. These values mean that in 95% of the cases, the building consumption will be between 121.4 (31.9) and 148.6 L (39.1 gal). Similar values are found after a mere 10 simulations, meaning that in fact, only 10 simulations of the building are required to get an adequate representation of the possible DHW demands.

Table 4.1. Variability of the building domestic hot water use profiles in L/day (gal/day) as a function of the number of profiles Generated

Number of building profiles generated	**Daily consumption per dwelling**			
	Average	**Standard deviation**	**Minimal**	**Maximal**
1	138.3 (36.4)	-	138.3 (36.4)	138.3 (36.4)
5	137.6 (36.2)	6.5 (1.7)	131.6 (34.6)	148.0 (38.9)
10	134.4 (35.3)	6.5 (1.7)	125.3 (33.0)	148.0 (38.9)
25	134.7 (35.4)	7.8 (2.0)	115.1 (30.3)	150.5 (39.6)
50	135.1 (35.5)	7.0 (1.8)	115.1 (30.3)	150.5 (39.6)
100	135.0 (35.5)	6.8 (1.8)	115.1 (30.3)	153.3 (40.3)

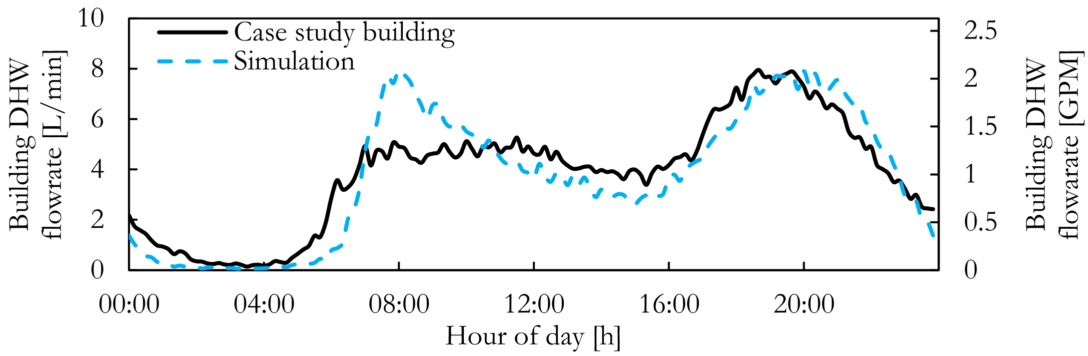


Figure 4.2. Average daily profile of DHW demand for the case study building according to measurements (full line) and simulations (dashed lines).

4.5 *Water heating system*

Generating accurate annual DHW consumption profiles is important for the design of water heating systems, but it does not directly provide adequate values for the storage tank volume and the heating capacity of the system. Therefore, another model which depicts the behavior of a water heating system was developed. Fig 5.3 offers a schematic representation of this model. It consists of a storage tank coupled with a heater. In the model, the flow of DHW asked by the occupants $\dot{m}_{DHW}$ comes either from the storage tank or from the heater at a supply temperature considered constant here at 60°C (140°F). Water comes from the aqueduct at a temperature of 10°C (50°F) to replace the volume of hot water lost in the system (either by DHW demand or by thermal losses). From there, it can take three different routes: 1) Go straight into the tank 2) Go to the heater so its temperature increases to 60°C (140°F) and then be directly sent to the building and 3) Go to the heater and then in the tank to be used later as hot water. The conservation of mass states that:

$$\dot{m}_{DHW} = \dot{m}_{q} + \dot{m}_{tank} \tag{5.3}$$

When $\dot{m}_{tank} > 0$, cold water is replacing hot water lost for DHW consumption whereas when $\dot{m}_{tank} < 0$, the tank is filled with hot water. As a result, the amount of hot water contained in the tank M, which physically cannot be negative or be larger than the size of the tank M_{tank}, is directly linked to $\dot{m}_{tank}$:

$$\dot{m}_{tank} = -\frac{dM}{dt} - \frac{dM_{loss}}{dt} \tag{5.4}$$

$$0 \leq M \leq M_{tank} \tag{5.5}$$

The term dM_{loss}/dt gives the rate of hot water in the tank that becomes cold due to heat losses. Its value was computed using an ambient temperature of 20°C (68°F) and a tank loss coefficient based on an insulation level of RSI-2.2 (R12.5), the minimal level of thermal insulation requirements of 2016 edition of ASHRAE Standard 90.1 [142]. The control strategy employed is a predictive one. At any time step, the controller records the amount of water consumed during a certain control period that follows the time step and then divides this quantity by the duration of the monitoring period:

$$\dot{m}_q = \rho\left(\frac{V}{\Delta t}\right)_k + \frac{dM_{loss}}{dt} \tag{5.6}$$

Here, the density of water ρ is constant at 997 kg/m^3 (62.24 lb/ft^3). As in ASHRAE guidelines, the designer decides of the duration of the control period – it can be as short as five minutes and as lengthy as a complete day. As explained before, a longer monitoring period requires a smaller heating capacity since consumption peaks are smoothen over a larger period, but on the other hand, it requires a bigger tank. If, for example, the monitoring period is k = 24 hours, then for every time step the controller divides the volume of DHW use in the following day by 24 hours to get the appropriate flowrate of water that should be heated. Knowing the DHW demand $\dot{m}_{DHW}$ and the heated flowrate $\dot{m}_q$, Eqs. (5.3) and (5.4) can then calculate the change in hot water volume in the tank. However, some adjustments for the flowrates might be necessary when the conditions defined by Eq. (5.5) are not respected (e.g. no hot water can be sent in the tank when it is already full). The final step is the calculation of the energy demand for the heater:

$$q = \dot{m}_q c_p \left(T_h - T_c\right) \tag{5.7}$$

Water thermal capacity c_p was also considered constant, at 4179 J/kgK (0.998 BTU/lb°F). In short, the water heating model asks for three inputs (i.e., annual profile of the demand of DHW by the occupants, duration of the control period and size of the storage tank) and returns two outputs: the annual profile of the volume of hot water in the tank and the one for the energy demand for the heater. The optimal tank size that prevent a lack of hot water for the occupants is determined by substracting the minimal value in the hot water volume profile to the maximal one and the optimal heat capacity of the system is simply equal to the maximal value found in the profile of heat demand.

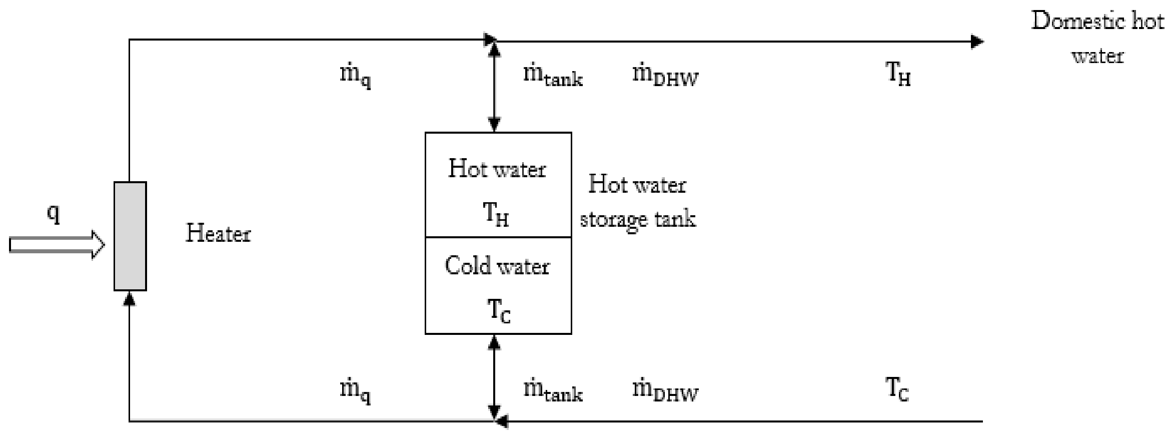


Figure 4.3. Schematic representation of the water heater system model used in this paper. The frontier between cold and hot water in the tank moves according to the amount of hot water.

This DHW system model was used to compute the required system sizing for the 100 generated profiles using 18 different control period durations (varying between 10 minutes and one day), resulting in 1,800 different designs for the case study building. In a scatter plot, these combinations form a consistent shape in which the DHW system should fall (see Fig. 4.4). There are differences between the figure made from ASHRAE guidelines (Fig. 4.4) and the one made from the model. For example, Fig. 4.4 says that a 2,000 L (526 gal) tank would demand a heat capacity of 63 kW (215 kBTU/h) for low consumers and 285 kW (972 kBTU/h) for high consumers. With the developed methodology, these values are respectively 40 (137) and 55 kW (188 kBTU/h), which suggests that the ASHRAE guidelines can lead to oversized water heating systems. Accordingly, the actual water heating system of the case study building also appears to be oversized.

With a heat capacity of 300 kW (1024 kBTU/h), the model says that a tank volume of 250 L (66 gal) would have been sufficient. This volume is approximately seven times smaller than the actual storage volume. Multiple factors can explain the high variations between the two water heating system design procedures: the use of safety fatctors in ASHRAE guidelines, the fact that DHW consumption is decreasing with the advent of low-flow devices and changes in habits, consumption differences between Americans and Canadians or an inaccurate estimation that the tank is 70% full of hot water in the ASHRAE methodology.

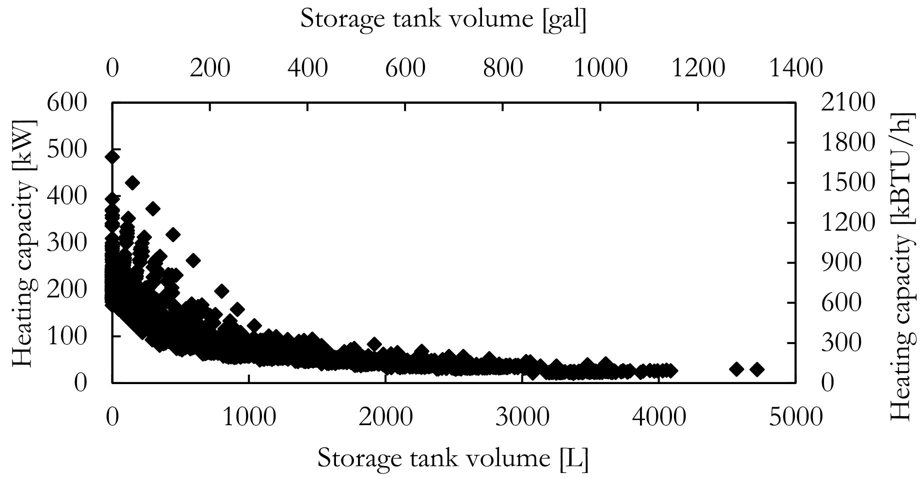


Figure 4.4. Hot water system design suggested by the model for different consumption profiles and peak durations.

4.6 *Design procedure validation*

The water heating model developed in this paper relies on a series of assumptions. The main simplification is the division of the storage tank in two distinct states for water (either 10°C or 60°C). In the proposed design procedure, it is considered that there is no lack of hot water if the amount of hot water in the tank does not drop to zero. In reality, if 10% of the water in the stratified tank is at a temperature of 60°C and the other 90% at 10°C, a thermal interaction between the two zones is likely to occur, resulting in DHW that might become too cold for the occupants. Therefore, the proposed water heating system for the case study building (a heater of 300 kW (1024 kBTU/h) linked to a tank of 250 L (66 gal)) was modelled with a dynamic simulation software [143]. The heater is controlled by a thermostat located in the lower part of the tank. Thermal stratification in the tank and heat losses from the tank and the pipes are all considered in this modeling. The software reads the measured annual DHW demand profile $\dot{m}_{DHW}$ of the building and returns the load temperature sent to the occupants. It was found that with this consumption profile, the minimal hot water temperature sent to the occupants is 47.8°C (118°F). However, an annual simulation showed that hot water temperature was under 50°C (122°F) for only 80 minutes over the year. These results desmontrate that the proposed design might work in the case study building without resulting in a lack of DHW for occupants.

4.7 *Conclusion*

This paper described two useful tools for the design of water heating system. The first tool generates DHW consumption profiles based on the occupancy of residential buildings. To create this tool, two occupant behavior models were merged together and then scaled to be applicable for Canadian lifestyle. The second tool presented uses annual DHW profiles, such as the ones generated by the first tool, to compute optimal hot water system designs. It was validated with a dynamic simulation software. These tools were tested on a multiresidential building in Canada. This evaluation showed that current ASHRAE guidelines tend to oversize hot water systems. In the case study building, the hot water tank was found to be seven times larger than it could have been. A more adequate design could lead to savings in terms of equipment costs and of materials used by the building, thus reducing both the building final bill and its environmental footprint. Also, this new methodology allows the designer to evaluate the compromise taken when deciding a given nominal capacity of the system in a quantitative manner.

CHAPITRE 5. ROBUSTNESS OF ENERGY CONSUMPTION AND COMFORT IN HIGH-PERFORMANCE RESIDENTIAL BUILDING WITH RESPECT TO OCCUPANT BEHAVIOR

Résumé

Étant donné le grand nombre de paramètres incertains, la simulation énergétique de bâtiments dépend de multiples hypothèses qui peuvent affecter la fiabilité des résultats. Le comportement des occupants est particulièrement incertain, surtout pour les bâtiments résidentiels où les gens passent la plupart de leur temps et sont libres d'agir comme ils le veulent. Les actions que les gens prennent à la maison ont un grand impact sur la performance énergétique d'un bâtiment et peuvent ainsi expliquer les mauvaises prédictions des simulations de bâtiment. Cette étude tente de quantifier l'impact des occupants sur la performance d'un bâtiment résidentiel en reliant différents modèles numériques de logement avec plusieurs profils réalistes de comportement des occupants. Les modèles numériques de logement ont été validés à partir de données recueillies auprès d'un bâtiment instrumenté. Les aspects du comportement des occupants qui sont couverts dans cet article sont l'occupation des logements, la consommation d'eau chaude et d'électricité, la température de consigne du système de chauffage et l'ouverture des fenêtres. L'impact individuel de ces aspects sur la demande en énergie et le confort thermique est analysé. Les résultats montrent une grande variabilité de consommation énergétique et de confort thermique pour un logement donné lorsque différents occupants y vivent. Les coefficients de variation des distributions obtenues sont autour de 50%. Les parcs immobiliers avec de nombreux logements sont moins sensibles aux occupants qu'un logement individuel, mais leurs niveaux de consommation demeure difficile à prédire en utilisant une approche déterministe pour représenter le comportement des occupants dans le cadre de simulations énergétiques.

Abstract

Due to the large number of uncertain parameters, building energy simulations rely on multiple assumptions that can affect the reliability of their predictions. Occupant behavior in particular is highly uncertain, especially for residential buildings where humans spend most of their time and are free to act as they want. The great variability of actions that occupants take at home has a great impact of the energy performance of a building and thus can explain the failures of building simulations to accurately forecast the energy consumption level of the building. This study aims to quantify the impacts of humans on the performance of a residential building by simulating dwellings using multiple realistic occupant behavior profiles. The numerical dwelling models were validated using monitored data from a case study building. Aspects of occupant behavior covered in this paper are occupancy, hot water and electricity consumption, heating set point temperature and openings of windows. The individual impact of all these aspects on energy demand and thermal comfort are analysed. Results show great variability of energy consumption and thermal comfort for a given dwelling when different occupants are living in it, with coefficient of variation of approximately 50%. Large housing stocks are less sensitive to occupant behavior than individual dwellings, but their consumption levels remain difficult to predict when using a deterministic approach to represent occupant behavior during a building energy simulation.

5.1 *Introduction*

Due to their large share of the global energy consumption and carbon emissions, there is tremendous pressure for buildings to become as energy efficient as possible. To reach the high expectations set by various energy efficiency schemes and building codes, building performance simulation is an important tool for building professionals during the design process. Unfortunately, the reliability of such simulations suffers from the large number of assumptions required, so the predicted energy consumption of a building comes with large uncertainties. As a result, actual building performance often significantly differs from the expectations set by numerical tools, a phenomenon called the "energy performance gap" [35], [37], [144]. While numerical simulation remains a powerful tool for comparing the performance of various building designs, some might question their overall reliability since their predictions often do not match well with the reality.

Assumptions made in building simulations relate to the weather, construction details (e.g.: infiltration rate, thermal bridges) and occupants (e.g.: control of windows) among others. The latter group of assumptions is particularly difficult to make since occupant behavior is a highly uncertain parameter with great "day-to-day" and "dwelling-to-dwelling" variability [145], [146]. This diversity of occupant behavior is observed for the use of the thermostat [147], of the electrical appliances [130], of lighting [148], of domestic hot water (DHW) appliances [68], [149], of windows [88], [150], of fans [151] and of blinds [152]. Consequently, it is not surprising that occupant behavior was found to be a major explanation for the energy performance gap of various buildings [50]–[52]. Occupants usually interact differently with the built environment than what was forecasted by the designer, leading to the building energy consumption being lower or higher than anticipated.

In spite of the high sensitivity of building performance with respect to occupant behavior [24], [153]–[158], designers usually base their calculations on a single predefined profile of users' behavior. This approach has the advantage of being simple, relying on easy-to-understand hypotheses regarding the occupants. However, with this approach, the diversity of occupant behavior is not represented, which means that the design of a building is based on a specific set of conditions rather than on all possible sets. For a given building design, such a deterministic approach provides only one level of energy consumption. In reality, this level of consumption can vary greatly due to the occupants. In other words, the robustness of a building's energy performance related to occupant behavior is often disregarded. It has been show before that a building system that is optimal for one profile of occupant behavior is not necessarily the optimal solution for most sets of occupants [98]. Selecting a non-robust building system can thus reduce the energy efficiency of the building. To prevent the choice of a design that has low robustness, building professionals can take their decisions by simulating various types of occupant behavior, especially with the recent development of realistic probabilistic behavioral models [100], [101], [159], [160].

Various studies on the sensitivity of building related to occupant behavior are found in literature, with most of them considering only one or two aspects of occupant behavior. For instance, De Meester studied the impact of humans in detached houses by considering 11 distinct simulations cases where the household size and the control of the heating system (set point temperature and schedule) were modified [156]. Different methodologies have been proposed, such as scenario analysis [161], [162], Monte Carlo simulation [163], point estimation [164] or Karhuen-Loève expansion [42]. Several of these methods use a rather simplistic representation of variability in occupant behavior. An example would be simulating the impact of the heating set point temperature with only two values – a high temperature (e.g. 24°C) versus a low temperature (e.g. 19°C) – and comparing the outputs to assess the importance of the parameter. This simple approach is useful, but has a very low resolution on the impact of the parameters. It might be possible to estimate the range of possible levels of energy consumption, but not to define the probability distribution function of energy consumption. Having information concerning this probability distribution function increases building professionals' capacity of predicting the real performance of a building.

In addition to assessing the robustness of buildings, stochastic building simulations with multiple profiles of occupants offer the possibility of quantifying the impact of each aspect of human behavior on the building's performance. Blight and Coley found that for a case study Passivhaus dwelling, increasing the set point temperature by 10% induces an increase of 37.9% of the consumption of heat [47]. Although statistically significant, windows openings and appliance, occupancy and lighting heat gains had a considerably smaller impact. Gaetani et al. applied a similar methodology on different variants of office building and found that the heating energy is sensitive to the set point, the use of artificial lighting and the use of blinds for most variants, but that it was sensitive to the presence of occupants and use of electrical equipment in only a few of the variants [165]. Ioannou and Itard found that the uncertainties related to the thermostat and the ventilation control of both class-A (high performance) and class-F (low performance) dwellings in Netherlands had substantially more importance on the heating demand of the dwellings than the uncertainties related to the thermal resistance of the envelope [17].

The objective behind this paper is to numerically assess the occupant behavior related to energy robustness of multiple apartments located within the same low-energy multifamily building. In order to measure the relative influence of occupants on energy consumption, their impact is compared to the one of the dwelling typology (i.e., floor level, façade orientation and thermal inertia provided by the envelope). The robustness analysis studies the impact of users on three outputs variables: the heating demand of the dwelling, its total energy use and the thermal comfort that is granted to occupants. The Monte Carlo method is employed to generate probability distribution functions for each of these variables. Five aspects of occupant behavior are studied: heating set point temperature, occupancy and household size, DHW use, electricity consumption and the control of windows. Different realistic occupant profiles, which represent the occupant behavior as multiple yearly schedules (occupancy, DHW, electricity…), were first generated and then used as inputs for building performance simulation models. These yearly schedules account for daily variation in the behavior of the occupants in one household and for variations in behavior from one household to another, meaning that all types of diversity in occupant behavior are considered.

The numerical models of the apartments are based on a case study building that has the particularity of having two distinct and symmetrical sections that use different wood wall assemblies: a light-frame (LF) one and one that relies on massive cross-laminated timber panels (CLT). As of right now, there is no consensus in literature found on the impact of thermal mass on the robustness of buildings energy performance with respect to occupant behavior. On one hand, the results of Hoes et al. indicate that a low thermal inertia wall that has a high window-to-wall ratio is the most robust solution in regard to user behavior [91]. On the other hand, a user-related robustness assessment from Buso et al. shows that the most robust building envelopes have large thermal mass [166]. This study allows for the direct comparison of light and heavy wall assemblies based on real data. Monitoring data suggests that there is no difference between the two types of wall assemblies in terms of total energy consumption, but dwellings in the CLT sections seem more prone to overheating in summer as shown in Chapter 3.

Section 2 summarizes the case study building used as the basis for the numerical models. These models are then described in Section 3, along with the methodology employed for their calibration and for the simulation of occupant behavior. Section 4 presents the results of this study, exploring the variability found between all simulations.

5.2 ***Case*** study building

The reference building is a high-performance multi-residential buildings that was built in 2015 and that is located in Quebec City, Canada. Quebec City is situated in ASHRAE climate zone 7 (classified as very cold climate). In Quebec, the average annual heating demand for an apartment building constructed within the last five years is 55.6 kWh/m^2 [167]. The case study building requires approximately 35 kWh/m^2 per year for heating. It is now inhabited by 90 people occupying the 40 dwellings of the building. There are four floors in the building and each of them has a floor area of 773.2 m^2.

The building is divided in two symmetrical sections that use different wooden structures. On one side, the walls have a wooden light frame (LF), the typical structure used for low-rise wood buildings in Quebec. On the other side, cross-laminated timber (CLT) panels act as the structure of the walls. The difference from a thermal standpoint is the higher thermal inertia of the envelope on the CLT side of the building. The external walls have the same thermal resistance in both sections (U-value of 0.157 W/m^{2}K), but the roof is more insulated for the light-frame section (U-value of 0.107 W/m^{2}K for LF, 0.138 W/m^{2}K for CLT). The CLT external walls are mainly comprised of brick (90 mm), polyisocyanurate (100 mm) and CLT (105 mm), whereas the light-frame walls consist of brick (90 mm), polystyrene insulation

(52 mm) and rock wool insulation (140 mm). On the fourth floor of the building, the brick façade is replaced by wood cladding panels. The roof is insulated by polystyrene (115 mm), polyisocyanurate (52 mm) and CLT (105 mm) in the CLT section and by cellulose (370 mm) for the LF section. Measured heat consumption show no tangible difference between the two sections of the building. Triple-glazed low-E windows with a U-value of 1.150 W/m^2K and a g-value of 0.56 were installed in the building with a window-to-wall ratio of 16.0%. The envelope has a high air tightness with an estimated 0.60 air changes per hour (ACH) at 50 Pa.

The building is heated thanks to a district heating hot water loop. Heat exchangers transfer energy from the district heating loop to the dwellings by radiators, each apartment having four radiators. The total overall heat transfer coefficient of these four radiators is 105 W/K. Air in the ventilation system is also heated to a tempered value of 20°C and no air recirculation is present. Solar walls and heat-recovery ventilator (HRV) units (recovery efficiency of 80%) also contribute to the heating of air in the ventilation system, which has a total flow capacity of 4,000 m^3/h (100 m^3/h per dwelling). There is an on/off switch in each apartment so that occupants can activate or deactivate the mechanical ventilation as they wish. No cooling system was installed in the building, meaning that the indoor thermal comfort in summer relies entirely on natural ventilation.

Since October 2015, the thermal behavior of eight of the 40 apartments of the building is thoroughly followed by a monitoring campaign. These dwellings are those situated on the eight corners of the building, meaning that four of them are on the first floor vs four on the top floor, and four are in the LF section vs four in the CLT section. Readers are referred to Chapter 2 to see a floorplan of the building with the position of the monitored dwellings. The indoor temperature in every room of those residential units was measured, in addition of the relative humidity [58]. In each dwelling, temperature sensors [168] were also installed behind the internal surface of the external wall, enabling the estimation of the wall temperature. The energy consumption is recorded by logging heat demand, DHW use and electricity consumption for each apartment (the heating demand and total energy use are also recorded for the 32 remaining dwellings of the building). For heating, the flowrate and the inlet and outlet temperatures [169] of the water entering the radiators of the dwelling are measured, which allows determining the energy consumed by these components. Sensors also provide information regarding the state (open/close) of every windows in the apartments [170]. All monitoring data are logged at a 10-minute frequency, except for the window states which is logged every minute. Weather data is measured every hour by a local weather station approximately two kilometers away from the building.

5.3 *Energy simulation of the dwellings*

5.3.1 Numerical models of the dwellings

Sixteen numerical models were created for dynamic simulations on TRNSYS [171]. This set of 16 models encompasses a model for each of the eight monitored dwellings and one for each of the dwellings in a hypothetical mirror image building (i.e.: a building in which the LF and CLT sections are reversed). This way, every combination of wall assembly, orientation and floor levels become possible. The models are identified in this paper first by their wall assembly (LF/CLT), then by their orientation (S/W/E/N) and finally by their floor level (1/4). For instance, LF-W-1 refers to the model of a light-frame dwelling located on the first floor and on the west corner of the building.

The dwelling thermo-physical models were defined in the TRNSYS simulation studio using the Type 56 component. The Type 1231 was put in the models to represent the radiators. Due to the high similarity of temperatures between all rooms of the apartments, a single thermal zone was considered for each numerical model. As a result, only one radiator is implemented in the model. Its heating properties are equivalent to the sum of the four radiators located in the real apartments. A PID controller adjusts the flowrate of water circulating into the radiator at an inlet temperature of 70°C.

Two distinct ventilation systems were implemented in the simulations: the mechanical one coming from the HVAC system and the natural ventilation created by the openings of windows. For the HVAC ventilation, a temperature gain from the solar walls is first computed by multiplying the solar radiation hitting the walls by a factor of 0.023 m^2K/W –

a ratio that was provided by the manufacturer [172]. Then, if the air temperature past the solar walls remains below -5°C, defrost is activated before sending the air into the 80% efficiency HRV unit to ensure that there is no freezing in the unit. Heating is then applied to the air exiting the HRV unit to step its temperature up to 20°C. An equation component replicates this process in the models and calculates the energy spent to defrost and heat the ventilation air. As for natural ventilation, another equation component was added in order to compute the volume of outdoor air entering the dwellings when a window is opened. The natural ventilation flowrate coming through the windows is calculated with the following correlation [173] :

$$q = \max\left(q_{wind}, q_{stack}\right) \tag{6.1}$$

where:

$$\begin{aligned} q_{stack} &= \frac{1}{3} A_{eff} C_d \sqrt{\frac{2hg\left|T_{in} - T_{out}\right|}{T_{out} + T_{in}}} \\ q_{wind} &= 0.025 A_{eff} V_{wind} \end{aligned} \tag{6.2}$$

The discharge coefficient C_d is assumed constant at 0.6 in this study. When the outdoor temperature is below the indoor temperature, q_{stack} is positive for dwellings on the first floor (outdoor air goes into the dwelling), but negative for top floor dwellings (indoor air comes out of the dwelling). The opposite happens when it is warmer outside than inside. The effective surface area of an opened window is equal to:

$$A_{eff} = H\left(H \sin\phi \cos\phi + W\left(1 - \cos\phi\right)\right) \tag{6.3}$$

where H is the height of the window, W its width and ϕ the opening angle of the window. In this paper, it was considered that ϕ remained constant throughout the year for all window openings – the value of ϕ being a parameter to be calibrated.

Energy related to DHW consumption is obtained by multiplying the volume of hot water with a ratio of 78.2 kWh/m^3, which is the ratio required to heat the water in the case study building. Internal heat gains (IHG) within the dwelling are proportional to the presence of occupants and to the consumption of DHW and electricity:

$$IHG = \alpha \cdot DHW + \delta \cdot Elect + \gamma \cdot Occ \tag{6.4}$$

In Eq. (6.4), the α, δ and γ coefficients are considered as unknowns and have to be calibrated. Dwellings and common spaces that are adjacent to the simulated dwelling are assumed to be at a constant temperature of 20°C. For first floor apartments, the ground under the floor is modelled by Type 77, which compute the ground surface temperature for all moments of the year. To easily fit the monitored data into the model during the calibration process, a simulation time step of 10 minutes was chosen, which required the interpolation of the hourly weather data. The selected timebase in Type 56 (i.e., the time step employed in the computation of the conduction transfer functions for the walls) was 30 minutes. This value must be as short as possible to ensure adequate dynamic simulation of massive panels in TRNSYS, but it is not possible to reduce it infinitely without introducing numerical problems [174].

The numerical models of the dwelling calculate every time step the heating power consumed by both the ventilation system and the radiators. After a simulation of a full year, the integration of the heating power profile gives the annual heating demand of the dwelling. The heating demand is summed with the consumption of DHW and electricity (provided to the models as inputs for IHG calculations) to determine the total energy use. Thermal comfort in the numerical dwellings is calculated by counting the number of hours during the year in which the indoor environment is not comfortable. Comfortable range for the indoor temperature is estimated with two distinct thermal comfort theories: the PMV/PPD model and the adaptive theory [175]. The latter is applicable to the case study building since it has no mechanical cooling, but can only be used for time steps when no heating is in operation and when the monthly mean outdoor temperature is between 10 and 33.5°C. If these two conditions are respected, the models use the adaptive theory for the computation of comfortable temperature ranges and if not the PMV/PPD model is employed. For the PMV/PPD model, it is assumed that metabolic rate and indoor air velocity are respectively 1.2 met and 0.1 m/s. As for the clothing factor, its value is a linear function of the indoor temperature based on Ref. [176]:

$$cl = -0.05T_{in} + 1.84 \tag{6.5}$$

Indoor environment is seen as comfortable if the PMV value is set within ±0.5 as prescribed by ASHRAE Standard-55 [175]. Thermal comfort in the numerical dwelling is thus measured by computing the number of hours of discomfort of the dwelling.

5.3.2 Calibration and validation of the models

The eight numerical models representing a real apartment were calibrated to make sure that their behavior was as close as the one observed for the real dwellings. To do so, monitoring data concerning the occupant behavior (DHW and electricity consumption, openings of windows, set point temperature) in the dwellings and the weather for the 2017 year were given to the models as inputs. The calibration process of the models compares the indoor temperature and the heat demand of the simulated dwellings with their measured counterpart and adjusts model parameters deemed as uncertain until a good match is found between the simulated and monitored datasets. For parameters in the models whose values were seen as uncertain, a calibration range of possible values was determined from handbooks or other similar sources. When it was impossible to find information regarding the uncertainty of a parameter's value (e.g., the zone air capacitance), the calibration range was set at ±20% of the initial value. This initial value was set to the best estimate provided by available information. The calibration function used to compare simulations with measurements was defined as the coefficient of variations of the root mean square error (CV(RMSE)):

$$CV\left(RMSE\right) = \frac{100\%}{\bar{m}}\sqrt{\frac{\sum_{i=1}^{n}\left(m_i - s_i\right)^2}{n}} \tag{6.6}$$

Simulation parameters to be calibrated were selected by executing a parametric test for all considered parameters. If the change in the calibration function observed within the calibration range of a parameter is below 5%, then the parameter was not selected for calibration. Considered parameters for calibration are listed in Table 5.1 along with their calibrated values for all dwellings.

Table 5.1. Values of calibration parameters after each model's calibration.

Calibration parameters	LF-N-1	LF-W-1	LF-N-4	LF-W-4	CLT-S-1	CLT-E-1	CLT-S-4	CLT-E-4
Cellulose conductivity [W/mK]	-	-	0.042	0.043	-	-	-	-
Rock wool conductivity [W/mK]	0.048	0.048	0.044	0.046	-	-	-	-
Polystyrene conductivity [W/mK]	0.035	0.034	0.037	0.034	-	-	0.035	0.036
Polyisocyanurate conductivity [W/mK]	-	-	-	-	0.026	0.028	0.027	0.028
CLT conductivity [W/mK]	-	-	-	-	0.111	0.111	0.113	0.110
CLT density [kg/m^3]	-	-	-	-	504	487	496	508
Winter shading Northeast façade [-]	0.47	-	0.42	-	-	0.51	-	0.37
Summer shading Northeast façade [-]	0.77	-	0.71	-	-	0.76	-	0.66
Winter shading Northwest façade [-]	0.40	0.37	0.42	0.34	-	-	-	-
Summer shading Northwest façade [-]	0.69	0.70	0.72	0.64	-	-	-	-
Winter shading Southeast façade [-]	-	-	-	-	0.38	0.37	0.33	0.31
Summer shading Southeast façade [-]	-	-	-	-	0.75	0.76	0.72	0.72
Winter shading Southwest façade [-]	-	0.37	-	0.42	0.40	-	0.35	-
Summer shading Southwest façade [-]	-	0.73	-	0.62	0.69	-	0.66	-
Winter window opening angle [°]	25.3	27.4	29.3	26.5	31.4	19.8	27.6	24.6
Summer window opening angle [°]	33.2	56.4	41.7	52.2	61.3	42.3	48.5	29.7
Winter infiltration rate [1/h]	0.113	0.117	0.086	0.084	0.113	0.106	0.089	0.092
Summer infiltration rate [1/h]	0.101	0.095	0.074	0.078	0.095	0.088	0.081	0.077
Zone air capacitance [kJ/K]	2630	2630	2580	2595	2630	2680	2540	2595
Electricity heat gain ratio [-]	0.86	0.78	0.79	0.82	0.80	0.73	0.88	0.81
DHW heat gain ratio [-]	0.24	0.19	0.31	0.22	0.17	0.32	0.22	0.24
Occupant heat gain ratio [W/occ]	113	106	118	111	121	108	114	112
Convective fraction of IHG [-]	0.88	0.91	0.82	0.79	0.84	0.85	0.91	0.81
Convective fraction of radiator heat delivery [-]	0.61	0.54	0.51	0.58	0.47	0.61	0.53	0.58
Radiator heating capacitance [kJ/hK]	134.3	119.5	132.2	126.5	123.3	120.5	127.4	124.6

The calibration is done for two weeks in winter (from 1st to 15th of February 2017). It is then repeated in the summer (from 1st to 15th of June 2017) for some parameters that might change from a season to another, such as the external shading factors. During the heating season (beginning of October to the end of April), these seasonal parameters take their "winter" value and then are switched to the "summer" one for the remaining months. The calibration procedure is an automated process using the genetic optimization software GenOpt [177]. GenOpt minimizes a cost function evaluated by an external simulation software and has shown in the past its abilities for the automated calibration of TRNSYS building models [178]–[180]. The algorithm used to minimize the calibration function is the hybrid generalized pattern search with particle swarm optimization algorithm.

The calibration process is done individually for all eight monitored dwellings. No contradictory results were found when comparing the calibrated values of all models. The thermal conductivity of the polystyrene insulation for example is similar between all models that shared this material. When the value of a calibration parameter depends on the location of the dwellings (e.g., infiltration rate, shading), the value found in each dwelling is used for this specific dwelling location in the building. For other parameters (e.g., density of CLT panels), the average value of all calibrated models sharing the parameter was used for the simulations of the 16 dwelling models.

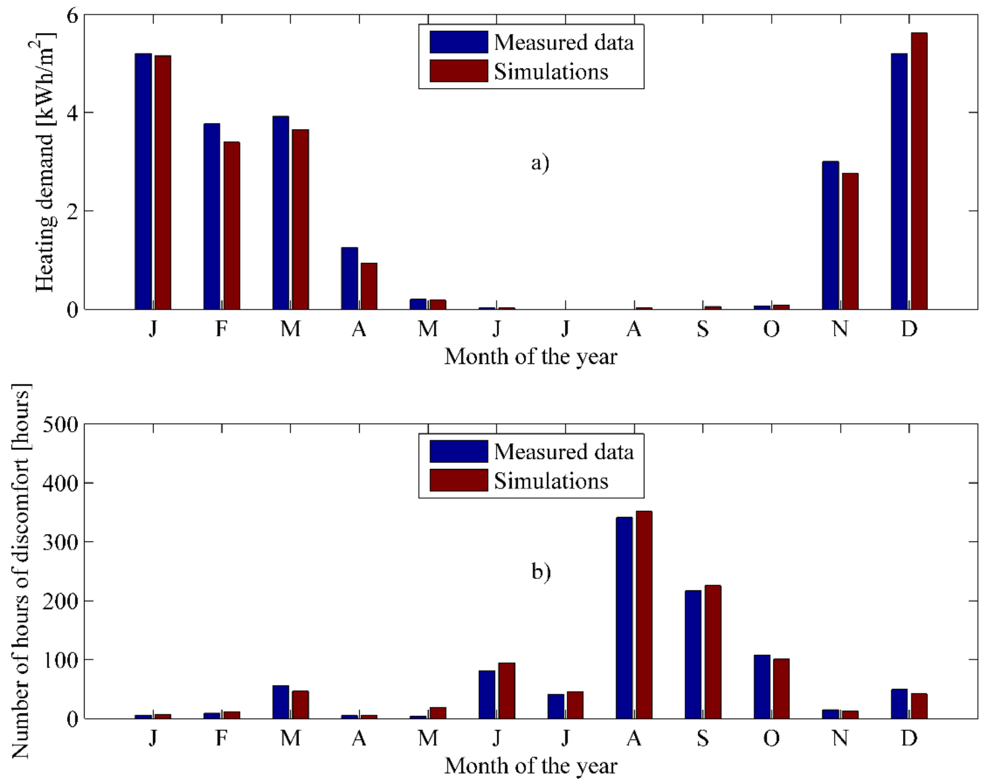


Figure 5.1. Monthly heating demand and number of hours of discomfort for dwelling CLT-N-4 according to simulated and measured data.

The resulting models were then validated by comparing the outputs of a simulation of the full 2017 year to the monitored data. Fig. 5.1 gives an example of a monthly comparison between a real and a numerical dwelling. Since this study focuses on annual output variables (heating demand, total energy use and number of hours of discomfort), a monthly criteria was chosen for the validation of the models instead of using an hourly criteria. The two validation indicators are the normalized mean bias error (NMBE) and the CV(RMSE). The CV(RMSE) indicator is computed using Eq. (6.6), except that a monthly time step is now used. NMBE can be obtained with:

$$\mathrm{NMBE} = \frac{100\%}{\bar{m}} \frac{\sum_{i=1}^{n} (m_i - s_i)}{n-1} \qquad (1)\ \ (6.7)$$

NMBE and CV(RMSE) for all calibrated models are shown in Table 5.2. All models respected the maximal values of ±5% for NMBE and 15% for CV(RMSE) as required by ASHRAE guidelines [181]–[183].

Table 5.2. Validation indicators for the eight numerical models. ASHRAE guidelines suggests a maximum of ±5% for the normalized mean bias error (NMBE) and of 15% for the coefficient of variation of the root mean square error (CV(RMSE)).

	Validation indicators	LF-N-1	LF-W-1	LF-N-4	LF-W-4	CLT-S-1	CLT-E-1	CLT-S-4	CLT-E-4
Heating demand	NMBE [%]	3.7	1.8	2.5	4.1	3.3	0.8	2.0	0.2
	CV(RMSE) [%]	11.9	3.4	8.7	13.4	9.4	2.4	6.4	1.2
Number of hours of discomfort	NMBE [%]	-3.2	2.1	-1.0	3.1	-2.1	0.4	-1.6	-0.5
	CV(RMSE) [%]	10.9	5.4	2.7	9.5	7.8	2.7	3.2	2.8

5.3.3 Stochastic simulation of occupant behavior

A total of 1,000 annual occupant profiles were stochastically generated and then provided to each of the 16 different dwelling models to generate probability distribution functions of energy consumption using a Monte Carlo method. Aspects of occupant behavior considered in these profiles are the active occupancy, the heating set point temperature, the consumption of DHW, the electricity use and the openings of windows in the dwellings. Active occupancy is defined here as the time steps in which an occupant is present at home, but not sleeping – he/she can interact with the built environment, but does not necessarily do so. The mentioned behaviors are considered as stochastic since human behavior at home vary day after day and is different from a dwelling to another. The active occupancy, DHW and electricity profiles were all obtained from the stochastic unified occupant behavior tool described in Chapter 4. This tool first assigns a household size for each simulation and then uses Markov-chains to create stochastic schedules of the number of active occupant in the dwelling for all time steps. Both DHW and electricity schedules are based on this active occupancy profile since there should be higher hot water and electricity demand when there are more people in the dwelling. "Type of occupant" factors drawn from probability distribution functions are attributed to each household to force a realistic "dwelling-to-dwelling" variability for the consumption of DHW and of electricity. As suggested in [184], continuous probability distribution functions are used to generate diversity in occupant behavior instead of clustering the occupants in different groups (low/mid/high consumer). In this study, a heating set point temperature is also given to each household. This set point is drawn from the distribution of set points used in Canadian homes [64]. The set point is treated as a static parameter that remains constant throughout the year – no programmable thermostat is considered due to the lack of data concerning their use.

A new stochastic window opening model was developed with the data coming from the eight monitored apartments. Stochastic window opening models are becoming increasingly popular over the years [185]–[187], but it was deemed preferable to use a new model built from the behavior observed in the case study building for three reasons. First, window models often require inputs that are not recorded in the building, such as the concentration of CO_2. Second, most models were developed using data obtained in Europe or East Asia. The behavior of people in those regions might vary from the one of Canadians due to differences in lifestyle and climate. The final and most important motivation for the construction of a new window model was to be able to add a "dwelling-to-dwelling" diversity in the control of windows. Models that include the diversity in window opening behavior are uncommon. Looking at the various behaviors found across the sample of eight monitored apartments, it became evident that households act differently regarding their windows. Fig. 5.2 showcases this by representing in a colormap the probability of a window being opened for different combination of indoor and outdoor temperatures. The dwelling described by the graph on the left has a relatively high probability of having a window opened and this probability is weakly related to the outdoor and indoor temperature. The probability of opened windows in the dwelling corresponding to the right side graph is also weakly linked with the temperatures, because its windows are nearly always closed – its use of windows is completely different than the one of the first dwelling. The graph in the center shows a great correlation behind windows opening and the temperatures, which is a behavior that deviates from the ones observed in the two others apartments.

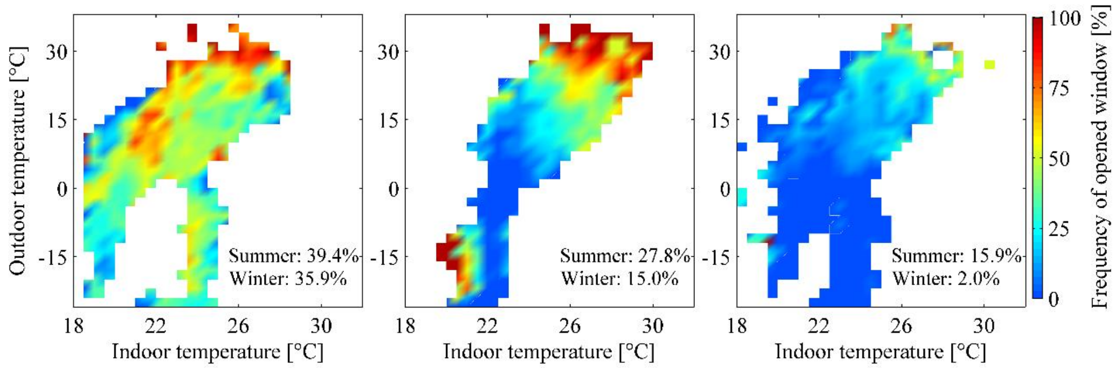


Figure 5.2. Colormap describing the link between the indoor and outdoor temperature and the probability of observing an opened window for three apartments in the case study building.

After preliminary tests, it was decided to develop change-of-state (window opening and closure) models instead of state (opened or closed window) models. State models could accurately predict the total time when the window is opened during a year, but they overestimated the number of changes of state by a factor of nearly 100. Therefore, a model to compute the probability of observing a window opening and one to compute the probability of observing a window closure was developed for each dwelling based on the logit regression:

$$\begin{aligned} \text{logit}\left(p_{op}\right) &= \ln\left(\frac{p_{op}}{1-p_{op}}\right) = \omega_{op,in} T_{in} + \omega_{op,out} T_{out} + \omega_{op,const} \\ \text{logit}\left(p_{clo}\right) &= \ln\left(\frac{p_{clo}}{1-p_{clo}}\right) = \omega_{clo,in} T_{in} + \omega_{clo,out} T_{out} + \omega_{clo,const} \end{aligned} \quad (6.8)$$

Only the indoor and outdoor temperatures are used to compute the probability of a window event. Other parameters, such as relative humidity and solar radiation, were found to be substantially less significant than these two parameters. Window opening models typically use the logit function to depict the link between the probability of an event happening and predictor variables. Regression analysis allowed for the estimation of the ω coefficients (see Table 5.3). These coefficients had different values from a household to another, again illustrating the diversity of window opening behavior. Instead of giving a value for each ω coefficient that is the same for all dwellings, it was assumed that the ω coefficients followed a normal distribution because of the window control diversity. The idea of drawing regression coefficients from normal distributions is replicated from [188]. The distribution of each coefficient was defined by each coefficient's mean value and standard deviation. However, since strong correlations were found between the ω coefficients, only $\omega_{op,in}$ and $\omega_{op,out}$ were randomly selected from their probability distribution functions. Values for other coefficients were directly calculated afterwards using the observed correlations found by regression analysis:

$$\begin{aligned}
\omega_{op,const} &= -27.2\omega_{op,in} - 98.5\omega_{op,out} - 1.42 \\
\omega_{clo,in} &= -0.30\omega_{op,in} - 1.07\omega_{op,out} - 0.04 \\
\omega_{clo,out} &= -0.17\omega_{op,in} - 1.01\omega_{op,out} \\
\omega_{clo,const} &= -2.18\omega_{op,in} + 80.7\omega_{op,out} - 3.37
\end{aligned} \tag{6.9}$$

Linking the coefficients together reduces the probability of obtaining an extreme combination of coefficients that lead to unrealistic use of windows, such as the probability of opening a window being equal to 1 throughout the year. The stochastic window model was tested by simulating window openings 10,000 times using the outdoor temperature and the indoor temperature profiles in the monitored dwellings. The overall frequency of opened windows in winter and summer from these 10,000 simulations are shown in Fig. 5.3, along with the measurements made from the monitored dwellings, each red mark corresponding to one monitored dwelling. The eight dwelling window control behaviors are mostly covered by the scatter plot formed by simulation results.

In the occupant behavior profile generator, it is ensured that the stochastic profiles are coherent with each other - there cannot be a window opening or a shower taken when no one is active in the dwelling. In addition to the 1,000 generated stochastics occupant profiles, two supplementary deterministic profiles were also used for the sake of comparison. The first deterministic profile (Deterministic profile #1) is equivalent to the one that a building professional would normally uses for a typical energy simulation of a residential building. It was based on the profile used by engineers to simulate the case study building during the design phase of its construction. These simulations were made with the PHPP software that was developed by the Passivhaus Institute for the certification of Passivhaus buildings [55]. The second profile (Deterministic profile #2) contains the daily schedules obtained when averaging all 1,000 stochastic profiles – it can thus be seen as the profile of the perfectly average occupant. Deterministic profile #1 was based on the occupant profile that was actually used in the design phase simulations of the case study building. The occupancy schedule in the deterministic profile #1 is directly taken from the recommendations of ASHRAE [189].

Table 5.3. Logit regression coefficients for the calculation of the probability of windows openings and closures for each monitored dwelling.

Dwelling	Window openings			Window closures		
	$\omega_{op,in}$	$\omega_{op,out}$	$\omega_{op,const}$	$\omega_{clo,in}$	$\omega_{clo,out}$	$\omega_{clo,const}$
1	0.10	0.03	-7.68	-0.11	-0.03	-1.83
2	0.02	0.04	-5.90	-0.15	-0.03	1.08
3	0.06	0.02	-6.72	-0.08	-0.02	-1.79
4	0.06	0.04	-6.69	-0.06	-0.03	-1.63
5	0.00	0.04	-5.66	-0.06	-0.05	-0.51
6	0.01	0.03	-4.92	-0.06	-0.05	-0.54
7	0.19	0.04	-10.09	-0.14	-0.01	0.04
8	0.03	0.02	-2.07	-0.07	0.00	-1.79
Mean	0.059	0.033	-6.216	-0.091	-0.028	-0.871
Standard deviation	0.062	0.009	2.296	0.037	0.018	1.073

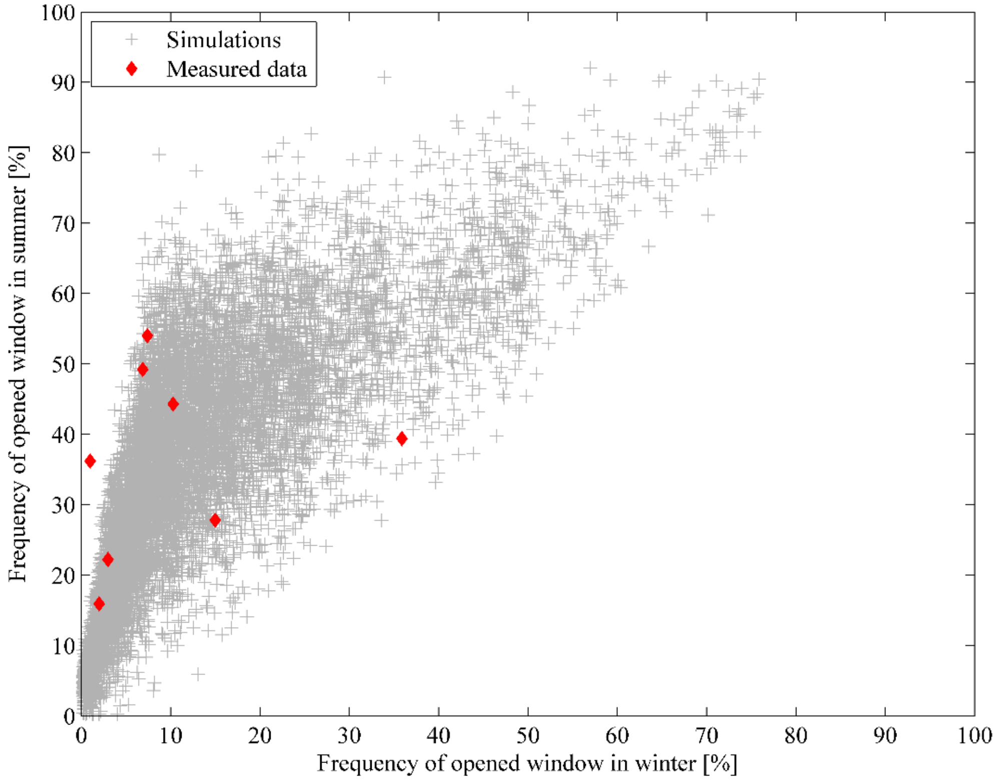


Figure 5.3. Scatter plot for the window opening behavior in winter and summer for the simulated and monitored dwellings.

5.4 *Results*

5.4.1 Energy performance robustness of a single dwelling

5.4.1.1 Measuring the energy robustness of a single dwelling

Energy performance robustness of a dwelling to occupant behavior is measured here by calculating the coefficients of variation (CV) of a dwelling's energy and comfort outputs using the 1,000 generated occupant profiles. The coefficient of variation is the ratio between the standard deviation σ and average value μ of a distribution. High coefficients of variation signify that the deviation of the energy distribution is large compared to its average μ, so the dwelling has a low robustness to occupant behavior – its performance can greatly change depending on occupants. Over all 16,000 simulations (i.e., 16 dwellings simulated with 1,000 occupant behavior profiles), the observed coefficient of variation is 61.2% for the heating demand (HD), 29.5% for the total energy use (TEU) and 74.5% for the number of hours of discomfort (NHD). These figures mean that the heating demand is more robust to occupants than thermal comfort, but less than the total energy use. Fig. 5.4 illustrates the overall distribution observed in all simulations for these three energy performance indicators. For the sake of simplicity, HD and TEU in this paper are displayed in terms of energy intensity (i.e., in kWh/m^2) instead of overall consumption (i.e., in kWh). For these three distributions, an important proportion of simulations are located near the bottom boundary of the distribution, meaning that they follow a lognormal pattern and are right-skewed. This right-skewness of the distributions suggests that the overall energy consumption of a housing stock is not necessarily driven by the consumption of the majority of its dwellings, but by its highest consuming households. For instance, HD is inferior to $\mu_{HD} + \sigma_{HD} = 59.0 \mathrm{kWh/m^2}$ for approximately 85% of simulated households. This subset has an average heating demand of 29.4 kWh/m^2 whereas the total population consumes 36.6 kWh/m^2. Consequently, the biggest 15% of consumers induces an increase of 24.5% of the μ_{HD} value for the population. Over the 40 dwellings in the case study building, HD ranges from 7.6 to 91.4 kWh/m^2 and the range for TEU is from 54.1 to 273.0 kWh/m^2. The order of magnitude of these ranges are roughly equivalent to the ones shown in Fig. 5.4.

The distributions of HD, TEU and NHD were also obtained separately for each apartment since part of the observed variations is caused by the different dwelling typologies (orientation, floor position, wall assembly). These distributions are presented in boxplots in Fig. 5.5. The high variability remains present in all dwellings, with $\overline{CV}_{HD} = 49.2\%$, $\overline{CV}_{TEU} = 27.6\%$ and $\overline{CV}_{NHD} = 74.0\%$. Accounting for the various dwelling typologies reduces the average coefficient of variation calculated for the heating demand, but only has small effects for energy use and hours of discomfort. Table 5.4 provides the mean values and coefficients of variation for different clusters generated from the 16 dwellings. Along with Fig. 5.5, this table provides information for the comparison of the energy performance of the dwellings. Dwellings on the fourth floor have subsequently lower needs for heating than those on the first floor, as observed during the monitoring of the building. Top floor apartments also appears more sensitive to occupant behavior than those on the first floor in terms of heating demand, but less sensitive regarding hours of discomfort. Orientation appears to have an effect on the heating demand, but this effect is considerably smaller than the one of occupant behavior. There is virtually no difference between LF and CLT dwellings, both in terms of average values and of variability. These results suggests that the addition of thermal mass has no significant thermal effect on the overall indoor environment in this particular building, but it is important to keep in mind the more insulated roof of light-frame dwellings on the top floor in the models and in the real building.

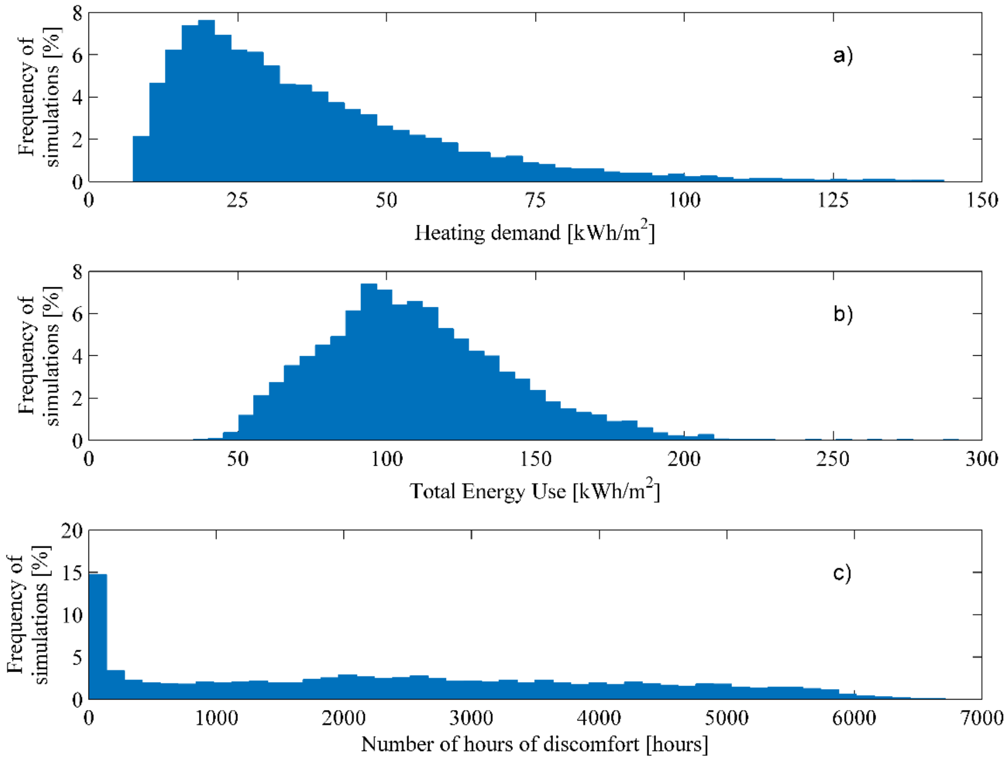


Figure 5.4. Distribution of a) heating demand, b) total energy use and c) number of hours of discomfort observed over the 16,000 simulations.

To see if there was any link between energy use and thermal comfort, Fig. 5.6 displays the 16,000 simulated results in a two-dimensional scatter plot showing on one axis NHD and on the other axis a) HD or b) TEU. In addition to the 16,000 simulations outputs, three other datasets are shown in Fig. 5.6: two generated from the two deterministic occupant profiles described earlier and the third one representing the measured values from the eight real dwellings. Looking at Fig. 5.6a, there does not seem to be a correlation between heating demand and number of hours of discomfort, but there appears to be what looks like a Pareto front on the left side of the scatter plot. The figure suggests that it becomes to some extent impossible to infinitely decrease the use of heating of a dwelling without inducing a rise of discomfort. There is also no obvious correlation between total energy use and thermal comfort.

Table 5.4. Average values and coefficients of variation of heating demand (HD), total energy use (TEU) and number of hours of discomfort (NHD) for multiple dwelling clusters.

		Average value			Coefficient of variation		
		HD	TEU	NHD	HD	TEU	NHD
Wall assembly	LF	36.2	109.8	2418.4	49.2	27.8	73.0
	CLT	37.0	110.6	2440.5	49.1	27.4	75.1
Floor position	1st floor	48.9	122.5	2388.8	45.9	24.1	81.4
	4th floor	24.3	97.9	2470.1	52.4	31.1	66.7
Orientation	South	30.6	104.2	2206.8	51.3	29.3	78.2
	West	36.9	110.5	2499.2	49.6	27.9	73.8
	North	40.0	113.6	2480.4	48.5	27.0	70.6
	East	36.7	110.3	2431.8	49.2	27.5	74.5

Points measured from the monitored dwellings all fall into the shapes generated by the scatter plots. These measured points also have great variability ($CV_{HD} = 57.8\%$, $CV_{TEU} = 27.6\%$ and $CV_{NHD} = 66.6\%$ for the measured dataset). This variability is not captured when using deterministic profiles, especially for the discomfort hours. In fact, the deterministic profiles greatly underestimated the potential presence of discomfort in the dwellings. The average number of hours of discomfort obtained from the PHPP and the average profiles respectively are 71.4 and 156.3 hours versus a measured value of 1692.9 hours. This implies that high discomfort is caused by extreme behaviors (e.g., low set point temperature, high consumption of electricity in summer…) and thus cannot be well captured when using averaged profiles that do not consider diversity in occupant behavior.

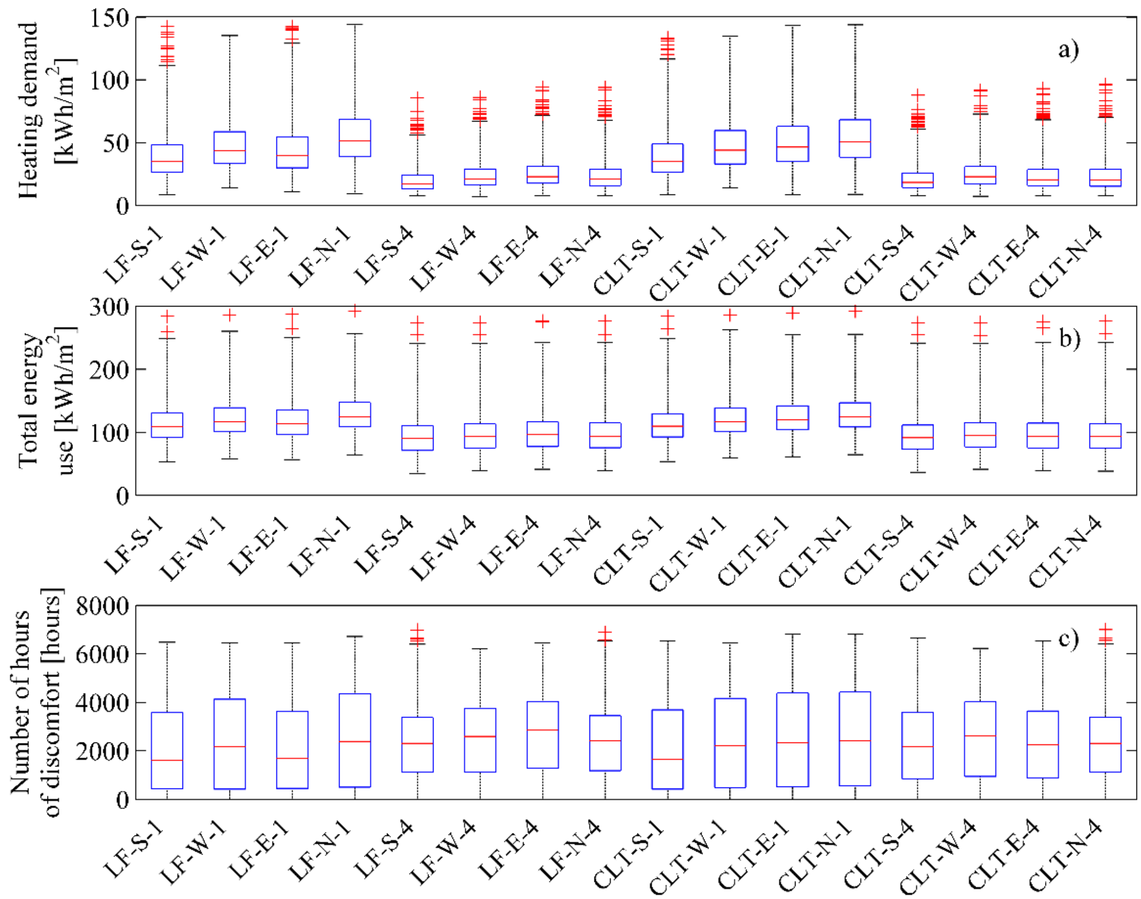


Figure 5.5. Individual distribution for each simulated dwelling of the a) heating demand, b) total energy use and c) number of hours of discomfort. Boxes limits represents the first and third quartile of the distribution. Red lines are the medians. Whiskers lengths cover 99.7% of data for a perfect lognormal distribution. Red crosses represent outliers assuming a lognormal distribution.

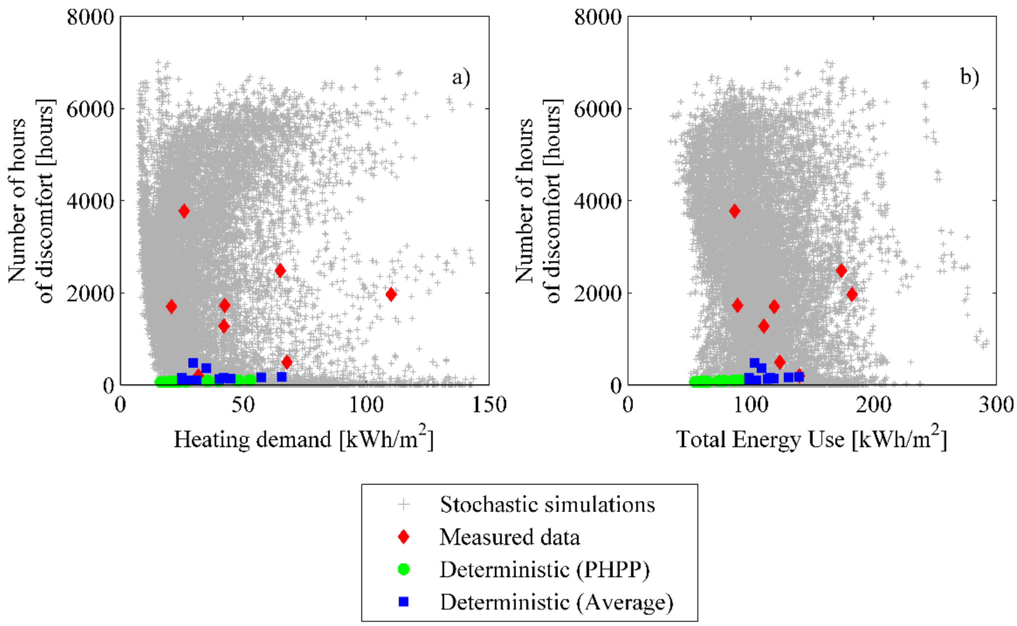


Figure 5.6. Scatter plot of a) the heating demand versus the number of hours of discomfort and b) the total energy use versus the number of hours of discomfort from stochastic simulations, monitored data and deterministic profiles.

5.4.1.2 Explaining the energy robustness of a single dwelling

To improve the energy robustness of a building, it is important to assess the reasons behind its high sensitivity to occupant behavior or, in other words, to quantify the impact of each aspect of occupant behavior on energy performance. Figs. 5.7 and 5.8 reproduce the scatter plots of Fig. 5.6 by dividing them in multiple grids of 30×30 pixels. The color of a pixel in a grid conveys the average value of an aspect of occupant behavior for all simulations that are located within the pixel (e.g.: in Fig 5.7b, the simulation profiles located in the first pixel from the left on the bottom row have an average temperature of 21.7°C). Blank areas in the figures are regions where no simulation landed on. Figs. 5.7a and 5.8a represent the number of simulations that fell within each of the pixel in the grids.

Multiple clusters of occupant behaviors that lead to different HD and TD values can be found in Fig. 5.7. There seems to be two types of behaviors that generate high discomfort – one on the left and one on the top of the grids. The first cluster of occupant behaviors is characterized by high occupancy and high consumption of electricity. The internal heat gains in these dwellings are so large that the indoor temperature is constantly above the acceptable range, even if the heating set point is moderate (average set point temperature of 20.5°C). The second non-comfortable cluster results from a combination of low heating set point, low occupancy and low DHW and electricity use. The indoor conditions of the dwellings in this region of the grid are too cold throughout the year.

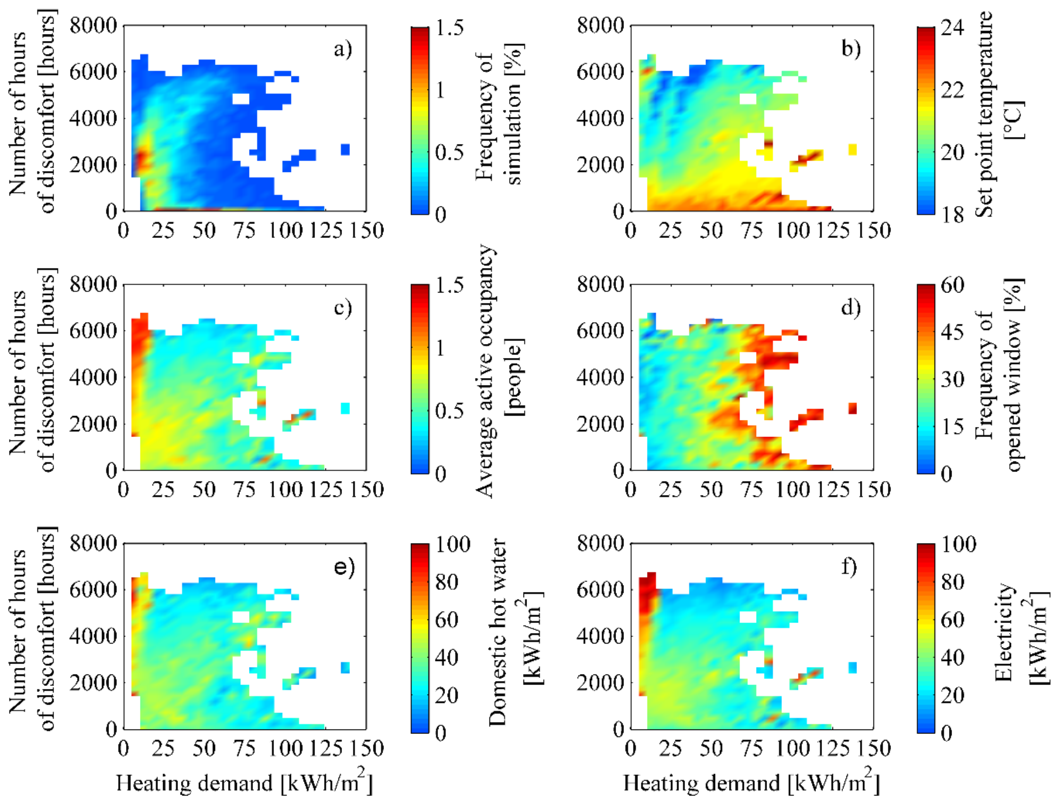


Figure 5.7. Colormap representing average values of various aspects of occupant behavior within the Heating-Discomfort two-dimensional plane.

The ideal behavior is the one that minimizes both energy use and discomfort (bottom left of the grids in Fig. 5.8). Very low use of windows (windows are opened on average for 7.4% for the year) are found in this region of the grids. The ideal region of the grids also has (on aggregate) low occupancy, DHW use and consumption of electricity. The average set point temperature found in the bottom left part of the grid is relatively high at 22.1°C, which is 1.3°C above the average set point temperature of Canadians [64]. This data expresses that ideal indoor environments can be obtained without requiring occupants to adopt extreme behaviors.

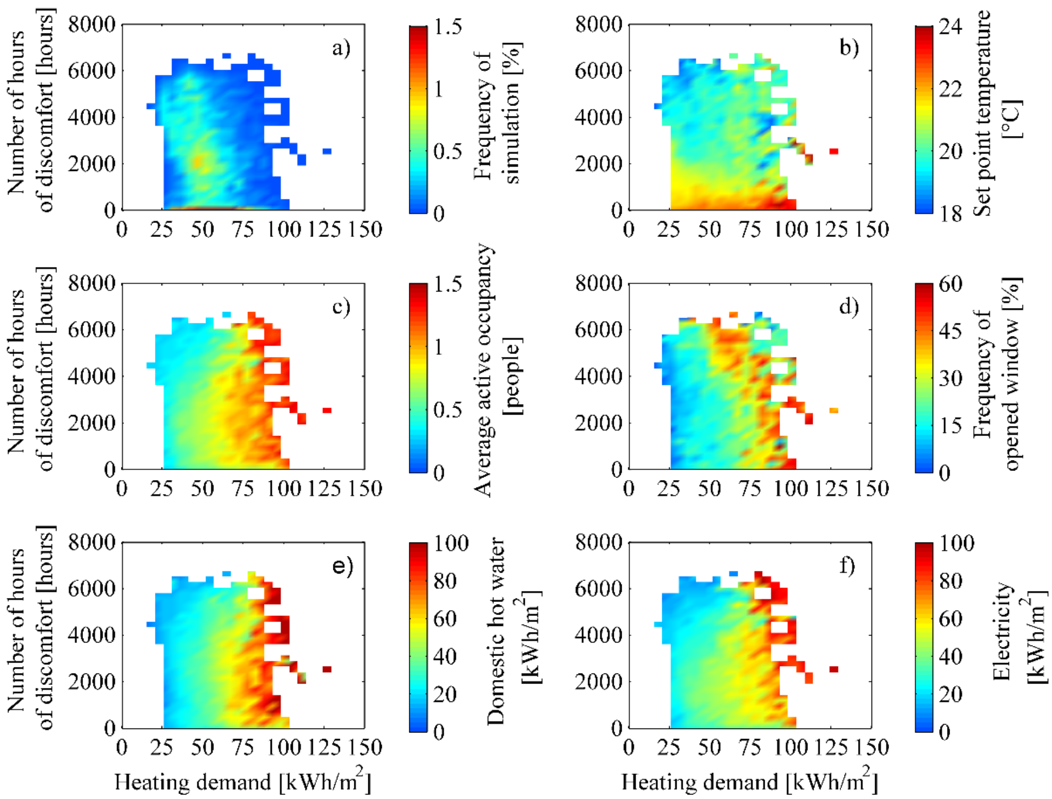


Figure 5.8. Colormap representing average values of various aspects of occupant behavior within the Energy-Discomfort two-dimensional plane.

Figures 5.7 and 5.8 are useful to qualitatively assess the interactions between the three performance variables and each aspect of occupant behavior, but it offers no quantitative information. Regression analysis can solve this issue by identifying the relationship between a dependent variable y and multiple independent variables x_j. Four multivariate linear regression models were built using data from the 16,000 simulations: one for the heating demand, one for the total energy use, one for the number of hours of "too cold" discomfort (NHCD) and one for number of hours of "too hot" discomfort (NHHD). The discomfort variable was divided here in "cold" and "hot" because an aspect of occupant behavior can have multiple effects on the total hours of discomfort. For example, as described before, depending on other independent variables, electricity consumption of a household can both increase and decrease the hours of discomfort of a dwelling. In a "cold" dwelling, electricity consumption adds internal heat gain that makes indoor environment more comfortable, but the opposite is happening in a “hot” dwelling: increasing the use of electricity will increase the indoor temperature and as a result lead to a less comfortable environment. When merely considering total discomfort, a linear regression model would fail to accurately see this correlation due to the conflicting links between electricity, “cold” discomfort and “hot” discomfort.

In a model with M independent variables, standardized multivariate linear regression models takes the following form [190]:

$$y^* = \sum_{j=1}^{M} \beta_j^* x_j^* + \varepsilon^* \tag{6.10}$$

where:

$$y^* = \frac{y-\bar{y}}{\sigma_y}, x_j^* = \frac{x_j-\bar{x}_j}{\sigma_{x_j}}, \varepsilon^* = \frac{\varepsilon}{\sigma_y}, \beta_j^* = \beta_j \frac{\sigma_y}{\sigma_{x_j}} \tag{6.11}$$

β_j^* represents the j^{th} standardized regression coefficient and ε^* expresses the model error (difference between predicted and observed data). Standardization is made to cancel the various units of measurement of the independent variables. Values for the regression coefficients are usually evaluated by minimizing the least square sum of the model errors. The standardized coefficients β_j^* assess the importance of each parameter on the model output, but also measure the linearity of the model since the closest the summation of the square of the standardized coefficients is to 1, the more linear the model is [72].

Figure 5.9 displays the nine parameters used in the four regression models along with their related standardized coefficients. The nine independent variables of the models characterize the occupant behavior in a dwelling in addition to its typology. The information related to the dwelling typology were expressed as dummy binary variables that are either zero or one (LF = 0 and CLT = 1; 1st floor = 0 and 4th floor = 1; Southwest façade = 0 and Northeast façade = 1; Southeast façade = 0 and Northwest façade = 1). Data regarding the dwelling typology were included in the analysis in order to confirm the observations made with the monitored data that the correlation between a dwelling’s typology and its thermal performance is mostly weak. The lack of correlations observed from the monitored data might be have been explained by the limited sample size of measurements (thus making the thermal performance of each cluster of typology prone to be influenced by the occupants), so it would be beneficial to see if similar conclusions can be obtained with calibrated simulations of the dwellings.

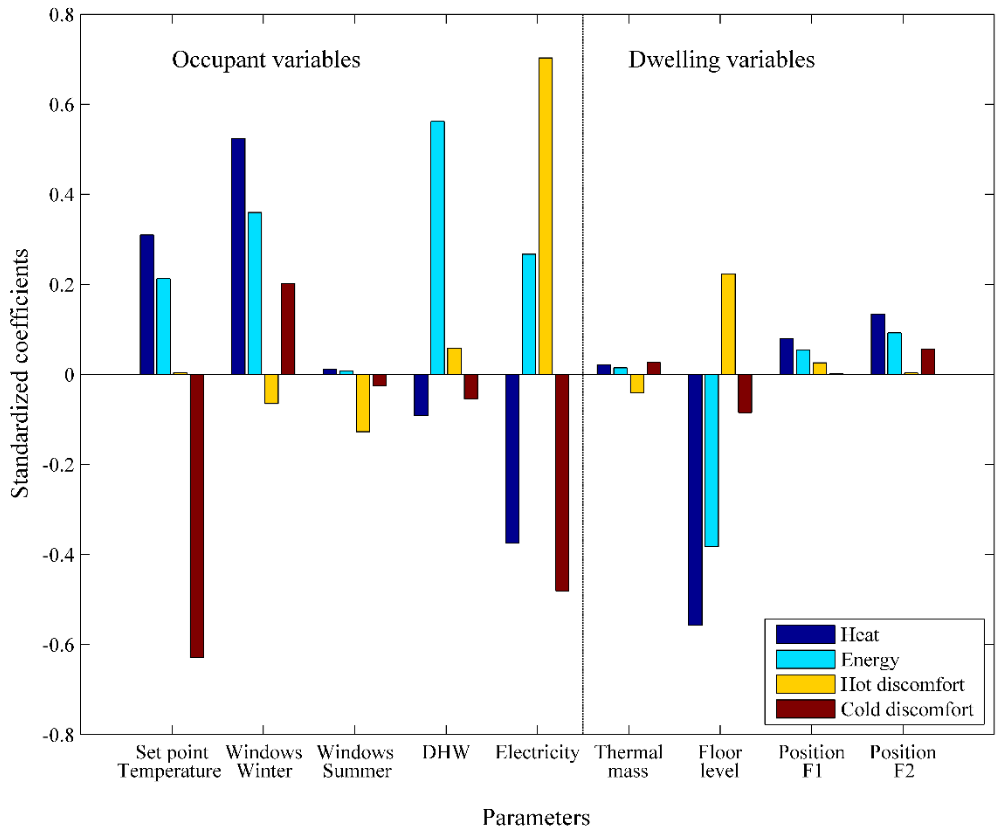


Figure 5.9. Standardized coefficients for each variables in the heating, energy and discomfort regression models.

The four considered dependent variables (HD, TEU, NHCD and NHHD) are affected differently by the different independent variables. Electricity consumption for instance leads to a decrease of heating demand and of cold discomfort (negative standardized coefficients), but to an increase of total energy use and of hot discomfort. The most important parameters for HD are the floor level of the dwelling (-0.55), the control of the windows in winter (+0.52), the consumption of electricity (-0.37) and the set point temperature (+0.31). It must be mentioned that the floor level parameter only compares the consumption of first and top floor dwellings, so its negative coefficient only conveys that top floor dwellings consume less than the first floor dwellings. The dwelling orientation (+0.08 and +0.13) has an influence on the heating need, but it appears far less important than the other mentioned parameters. TEU depends greatly on DHW activity (+0.56), floor level of the dwelling (-0.38), the control of the windows in winter (+0.35), the consumption of electricity (+0.27) and the set point temperature (+0.21). Electricity has notably less influence than DHW on total energy use due to the fact that it contributes directly to the reduction of the heating demand.

Although opening windows in winter is detrimental for the energy intensity of a residential building (as observed in Fig. 5.8), this is not the case when opening the windows during the summer. In fact, according to the model, windows opening during summer is the third most important parameters for the reduction of hot discomfort (-0.13), behind electricity consumption (+0.70) and floor level of the dwelling (+0.22). The coefficients for the change in wall assembly are statistically insignificant for all energy performance indicators. The energy intensity of a dwelling and its thermal comfort do not seem to be affected by the presence or absence of thermal mass within the dwelling envelope. In general, occupant variables are more important than the variables related to the dwelling typology, which tends to agree with measurements. If the same exercise was replicated with a deterministic approach (i.e., using the dataset from one of Deterministic profile #1 or #2), it would not have been possible to see the variance in thermal performance that is due to occupants. Most of the variance would have been included into the dwelling typology variables, making them more statistically significant than they are according to the Monte Carlo approach.

To make sure that the obtained coefficients are reliable, three indicators were used to assess the performance of the regression models: (i) the coefficient of determination R^2 of the regression model, (ii) The F-test value for overall significance of the model and (iii) The summation of the square of β_j^* to measure the models' linearity. The values of these indicators for all four models are available in Table 5.5. Although models reproducing heating demand and total energy use have high R^2 values and high significance, the results for the discomfort models are more mitigated. A possible explanation could be the assumption of linearity in the correlations between the comfort variables and each of the nine independent variables. This explanation is reinforced by the fact that discomfort models have a noticeably low sum of squares of β_j^*. Nonetheless, due to the large number of observations in the regression models (n=16,000), the p-value related to each F-test is below 0.0001, proving the great statistical significance of the four regression models. Improving the two discomfort models could thus modify the standardized coefficients, but it would be surprising to observe large changes (e.g.: electricity would still be expected to have a high influence on hot discomfort). Therefore, Fig. 5.9 can be seen as a guide that provides a general idea of where efforts should be concentrated to minimize heating demand, total energy use and discomfort in residential buildings.

Table 5.5. Performance indicators of the regression models for the heating demande (HD), total energy use (TEU), number of hours of cold discomfort (NHCD) and number of hours of hot discomfort (NHHD).

Performance indicators	HD	TEU	NHCD	NHHD
R^2	0.864	0.936	0.698	0.588
F-test	900	2062	327	202
$\sum \beta_j^*$	0.852	0.719	0.681	0.570

5.4.2 Measuring the energy robustness of a housing stock

High diversity of occupants leads directly to high diversity of energy demand for a single dwelling, so the energy consumption and thermal comfort are difficult to predict before occupation as shown in Section 5.4.1. However, one would expect these variables to become more predictable for a housing stocks of multiple dwellings (e.g., multiresidential buildings, districts) since it is statistically easier to forecast the expectation and deviation of a probabilistic process when the sample is large. In a large housing stock, the energy demand required by a high consumer is amortized over a large number of dwellings, so its impact on the overall demand of the stock is minimal. Therefore, large housing stocks should be more robust in terms of energy performance with respect to occupant behavior.

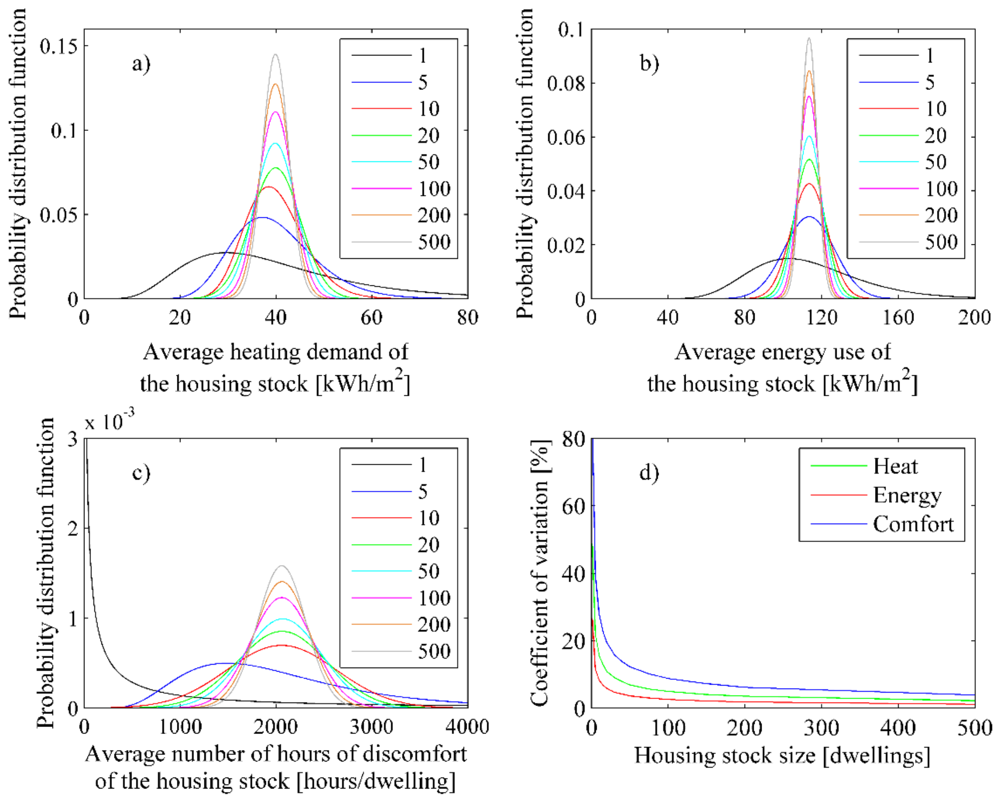


Figure 5.10. Distribution of a) heating demand, b) total energy use and c) number of hours of discomfort for housing stocks of 1, 5, 10, 20, 50, 100, 200 and 500 dwellings, along with d) the coefficient of variation of the distribution as a function of housing stock size. The legends in the first three plots display the housing stock size.

This hypothesis was tested by considering the energy and comfort distribution obtained from housing stocks of 1, 5, 10, 20, 50, 100, 200 and 500 dwellings. For each of these housing stock sizes, 10,000 combinations were randomly chosen from the 1,000 simulations of a given dwelling. Similar tests were done for all dwellings and yielded similar conclusions, so only results coming from LF-S-1 are presented for the sake of conciseness. The total HD, TEU and NHD was recorded for each of the 10,000 combinations, allowing the computation of probability distribution functions for the housing stock energy use and discomfort. These probability distribution functions are available in Fig. 5.10. The widest probability distribution function on each subplot corresponds to the distribution for a one-dwelling housing stock and then the distributions becomes narrower as the housing stock increases – the most cramped distribution being the one for a 500-dwelling housing stock. Small housing stocks follow lognormal distributions, as seen earlier in the paper, but the distributions become normal for large numbers of dwellings In housing stocks of 500 dwellings, the coefficient of variation is 2.3% for heating demand, 1.2% for total energy use and 3.9% for hours of discomfort. These coefficients of variation are approximately 22 times smaller than those of the one-dwelling set. The size of a housing stock is thus an important parameter for its energy performance robustness to occupants.

Figure 5.8d illustrates the link between the energy robustness of housing stocks and their number of dwellings. From a set of one dwelling to 10 dwellings, coefficients of variation quickly fall. Afterwards, their values slowly reduce asymptotically. For example, the coefficient of variation for the heating demand is 50.1% for one-dwelling stock, 15.8% for 10-dwelling stocks, 11.2% for 20-dwelling stocks and 5.0% for stocks of 100 dwellings. Since large housing stocks are more robust to occupant behavior, one could think that their consumption levels are more predictable and thus could be estimated using one single deterministic profile. This profile could yield the μ parameter of the distribution and the σ parameter could then be estimated with Fig. 5.8d. However, it remains important to account for diversity between the different dwellings of the housing stocks for multiple reasons. First, the link between the coefficient of variation and the housing stock size could be different for a building with different envelope and HVAC systems than the ones of the case study building. Therefore, the coefficient of variation given by Fig. 5.8d might be different for another type of building. Another reason as to why deterministic profiles might not accurately find the distributions of large housing stocks is that it is difficult to identify a deterministic profile that will provide the μ parameter of the distribution. Even using a deterministic profile based on the average schedules computed from all stochastic occupant behavior profiles is not sufficient since this averaged profile neglects multiple interactions between the built environment and the various aspects of occupant behavior. For dwelling LF-S-1, the averaged profile underestimated the average heating demand of the stochastic profiles by 22.8%, underestimated the total energy use by 8.0% and the hours of discomfort by 95.3%. In short, large housing stocks are more robust to occupants than small housing stocks, which probably means that fewer occupant profiles would be necessary in a Monte Carlo simulations to estimate the distribution of possible consumption levels. However, the few required simulated runs for large housing stocks still ask for diversity to be accounted for between the various dwellings contained in the stock since it is difficult to find a single deterministic profile to use for all dwellings in the housing stock that can identify the stock's average consumption.

5.5 *Conclusions*

Monte Carlo simulations of occupant behavior in dwellings demonstrated the high sensitivity of a residential building's energy and comfort performance. The simulations were based on numerical models that were calibrated and then validated using data measured from a case study building. High variability was observed for heating demand (average coefficient of variation of 49.2%), total energy use (27.6%) and hours of discomfort (74.0%) for a given dwelling when the occupant living in it were virtually "changed". Heating demand is specifically sensitive to the set point temperature, the control of windows and the consumption of electricity. Changes in these occupant behaviors generate changes in the heating demand. DHW consumption is also important when calculating the total energy use of the building. The heating set point temperature, electricity use and window openings behavior are the main occupant parameters impacting thermal comfort. In the perspective of raising occupants' awareness to their impact on buildings performance, these aspects should be focused on. As for the dwelling parameters, the floor level of the dwelling was found to be significant for the heating demand and the number of hours of discomfort. The impact of orientation and thermal inertia were mostly insignificant when compared to the influence of occupant behavior. This reinforces the view that building professionals should have a proper understanding of the actions taken by occupants at home. Housing stocks with hundreds of dwellings are unsurprisingly more robust to occupants than single dwelling, making their energy consumption easier to predict. However, it remains difficult to find beforehand a deterministic profile that can forecast the average consumption of the housing stock.

The distributions for energy consumption and thermal comfort shown in this study could be even broader since some aspects were not considered due to the lack of data: programmable thermostat, control of the mechanical ventilation system (on/off), use of blinds, etc. On the other hand, it is also possible that the distributions slightly overestimate the variability since the windows control model developed in this paper extrapolates the diversity in window opening behavior of the total population from the behaviors measured in eight dwellings. The developed model is thus prone to be influenced by "outlier behavior" found in this small dataset. The assumption of normality for the probability distribution functions of the coefficients in the windows opening models has also not been thoroughly validated. More monitoring studies on the diversity on window opening behavior are necessary to solve these issues.

There are still a lot of challenges and opportunities for research on the impact of diversity of occupant behavior on the energy and comfort in residential buildings. The results presented in the paper cannot be generalized for all buildings since they are based on a case study building. The sensitivity of energy performance to diversity of occupant behavior can vary for different types of buildings. Nonetheless, the study shows the great importance of appropriately considering occupant behavior in building simulations. Providing a range of possible energy consumptions levels for a building design appears as a more realistic expectation for building simulations than providing a unitary value of the building energy consumption. Doing so could reduce the energy performance gap and increase the reliability of simulations.

Conclusions

Cette thèse avait comme principal objectif d'approfondir notre compréhension de la consommation énergétique et du confort thermique des bâtiments résidentiels en bois à haute performance énergétique, en mettant l'emphase sur le rôle joué par les occupants. Trois axes de recherche ont été établis pour atteindre cet objectif : le suivi de la performance énergétique d'un bâtiment réel, la création d'un outil centralisateur du comportement des occupants et la considération de la diversité des comportements des occupants lors de la conception de bâtiments. Les sous-sections qui suivent résument les principales contributions de cette thèse en lien avec la mise en place de bâtiments à faible consommation énergétique. Une liste de travaux futurs reliés aux points dégagés lors de cette thèse est également présentée.

Suivi de la performance d'un bâtiment multirésidentiel

Par le suivi des *Habitations Trentino*, nous en avons appris sur son comportement énergétique. Les grandes différences de demandes énergétiques entre les quarante logements du bâtiment sautent aux yeux. Chez le plus petit consommateur, on demande un total 54.1 kWh/m^2 par année versus 273.0 kWh/m^2 pour le logement ayant les plus grands besoins énergétiques. Ces logements utilisent pourtant les mêmes systèmes architecturaux et d'ingénierie. Outre le fait que les appartements au premier étage ont une demande en chauffage plus grande que celle mesurée sur les trois autres étages du bâtiment, les différences de consommation observées ne s'expliquent pas par la position du logement; l'orientation n'apparait pas comme un prédicteur important de la demande en chauffage d'un appartement. La taille du ménage vivant au sein de l'appartement est aussi un paramètre n'ayant qu'une faible corrélation avec sa consommation totale d'énergie. Le type de consommateur vivant dans un logement est ainsi un élément important dans le bilan énergétique du logement.

Les variations inter-logements sont non seulement présentes pour la consommation énergétique, mais également lorsqu'on compare la présence de surchauffe. Pendant l'été, certains logements ont régulièrement un environnement intérieur trop chaud pour être considéré comme étant confortable selon les standards. D'autres logements ne vivent pas ce problème. Parmi les logements les plus chauds, on dénote que 57% de la saison estivale il y a de la surchauffe. Cela montre qu'il est important d'envisager ce problème lors de la conception de bâtiments n'ayant pas de climatisation. Un fait important en lien avec les risques de surchauffe est que dans le climat québécois, la température de l'air extérieur est rarement supérieure à celle de l'air intérieur. L'extérieur représente ainsi le contrepoids idéal pour balancer la température intérieure. Les bâtiments à haute performance énergétique sont habituellement fortement isolés et très étanches, ce qui réduit énormément le transfert thermique entre l'intérieur et l'extérieur. Bien que ce faible transfert soit bénéfique en hiver pour limiter les dépenses en chauffage, il engendre plus de surchauffe en été. Des stratégies d'évacuation de la chaleur, reposant principalement sur une optimisation de la ventilation, doivent être réfléchies lors de la conception de tels bâtiments pour assurer un confort estival acceptable.

Pour mesurer l'importance de différents paramètres sur le comportement thermique du bâtiment, des modèles statistiques ont été développés à partir d'analyses de régression linéaire. Certains modèles s'attardaient à projeter la demande en chauffage d'un logement pour une journée donnée alors que d'autres évaluaient plutôt la température de l'air dans les appartements durant l'été. Les prévisions de ces modèles correspondaient généralement bien avec les mesures, montrant l'habileté de tels modèles à reproduire le comportent d'un bâtiment. En comparant l'impact des différents paramètres, certains se distinguaient autant pour l'énergie consommée en hiver que pour le confort en été : la température extérieure, la consommation d'électricité ainsi que l'ouverture des fenêtres. Les deux dernières variables sont entièrement contrôlées par les occupants des logements. Un comportement différent vis-à-vis une de ces deux variables mène à différents niveaux de demande en chauffage et de confort thermique pour un logement donné, ce qui explique les grandes variations inter-ménages observées sur l'ensemble des logements.

En termes de demande de chauffage, les données ne montrent pas de différences notables entre les appartements ayant une structure légère de bois et ceux misant sur les panneaux massifs de CLT. L'ajout de masse thermique ne semble pas modifier la quantité globale de chaleur à fournir aux logements. Par contre, les appartements en CLT sont plus chauds en été et donc moins confortables que ceux en ossature légère. Cette disparité peut cependant être expliquée par le fait que le bloc en ossature légère soit plus ombragé durant l'été que le bloc en CLT. Ce dernier a aussi une orientation plus rapprochée du Sud.

Un aspect qui distincte *Les Habitations Trentino* des bâtiments résidentiels typiques est la faible part que prend le chauffage des espaces dans la répartition de la consommation énergétique. Environ 29% de la demande en énergie du bâtiment étudié est consommé par les radiateurs et par les serpentins de chauffage des systèmes de ventilation. Habituellement, environ 60% de l'énergie consommée par les bâtiments résidentiels est due au chauffage des espaces. Cette différence montre l'effet des mesures prisent pour minimiser la demande en chauffage des *Habitations Trentino* : le rôle du chauffage dans le bilan énergétique diminue et cède du terrain à la consommation d'eau chaude et l'utilisation de l'éclairage et des appareils électriques.

Élaboration d'un modèle stochastique des occupants

Différents modèles stochastiques simulant le comportement des occupants dans les bâtiments résidentiels sont disponibles dans la littérature. Toutefois, il est fréquent que ces modèles soient limités par au moins un des manquements suivants: 1. Le modèle ne simule qu'un seul aspect du comportement des occupants, 2. Le modèle se base sur des données provenant d'un seul pays, donc peut ne pas fidèlement représenter le comportement de gens ailleurs dans le monde et 3. La diversité inter-ménage n'est pas considérée. La thèse tente de pallier à ces problèmes en rassemblant quatre modèles existants en un outil centralisateur qui peut générer des horaires stochastiques de présence des occupants ainsi que de la consommation d'eau chaude et d'électricité dans un logement. Des facteurs d'ajustement sont appliqués pour considérer les modes de vie variables d'un pays à l'autre ainsi que la diversité inter-ménage de comportement des occupants.

L'outil a été validé en comparant ses résultats aux comportements adaptés par les occupants des *Habitations Trentino*. Cette validation a montré que les changements apportés aux modèles existants ont globalement été bénéfiques pour prédire la quantité totale d'eau chaude et d’électricité consommée dans le bâtiment, les moments où cette consommation est effectuée et la variabilité de consommation d’un logement à un autre. Néanmoins, certaines différences demeurent entre les simulations et les mesures. D’abord, il n’y a pas vraiment de pointes de consommation observées le matin dans *Les Habitations Trentino*. De plus, la variabilité de consommation d’eau chaude entre les logements demeure sous-estimée. Cette sous-estimation est principalement due au fait que la corrélation entre la consommation d’eau chaude d’un logement et le nombre de personnes qui y habitent est significativement plus forte dans *Les Habitations Trentino* que ce qui est noté dans d’autres bâtiments décris par la littérature.

Puisque le contrôle des fenêtres (ouverture/fermeture) varie beaucoup entre les logements, un autre modèle stochastique a été développé afin de traiter cet aspect du comportement des occupants. Ce second outil est conçu à partir des données provenant du bâtiment étudié. Dans le cadre de simulation de bâtiments, ce modèle de contrôle des fenêtres peut être fusionné à l’outil centralisateur afin de s’assurer qu’il n’y ait pas de changements d’état de fenêtre durant les pas de temps où aucun occupant est supposé est actif dans le logement.

Étude de l’influence des occupants sur les bâtiments résidentiels

Lors de la conception de bâtiments, la diversité du comportement des occupants est habituellement négligée. Des profils typiques d’occupants basés sur des moyennes sont souvent utilisés pour représenter les occupants dans les simulations énergétiques de bâtiments. Étant donné la grande influence que les occupants peuvent avoir sur la performance d’un bâtiment, cette hypothèse d’un comportement typique peut affecter la justesse des résultats de simulation. La thèse a donc étudié comment les différents comportements des occupants peuvent influencer la performance globale de logements ainsi que le dimensionnement de systèmes mécaniques.

Des modèles numériques de certains appartements des *Habitations Trentino* ont été créés sur le logiciel TRNSYS. Pour que ces modèles se comportent comme les appartements réels, ils ont été calibrés à partir des données mesurées. En fournissant différents profils de comportement des occupants aux modèles de logement, on remarque que la demande en chauffage d'un logement, sa consommation totale d'énergie et son confort thermique sont très sensibles aux gestes posés par les occupants. L'emploi de profils typiques d'occupants ne permet pas de capter cette importante sensibilité et ainsi de reproduire la variabilité inter-ménage qu'elle cause. Les parcs immobiliers contenant de nombreux logements sont plus robustes vis-à-vis le comportement des occupants. En effet, les aspects probabilistes du comportement des occupants s'annulent à mesure que le nombre de logements contenus dans le parc augmente. Il ne demeure toutefois pas évident de trouver un profil typique des occupants qui donne exactement la consommation moyenne des logements contenus dans un vaste parc immobilier.

Un modèle de régression linéaire a été formé avec les résultats de simulation pour expliquer la grande variabilité de performance énergétique et de confort thermique observée dans les logements. La demande en chauffage est particulièrement sensible à l'étage où se situe un logement, au taux d'ouverture des fenêtres en hiver, à la consommation d'électricité et à la température de consigne. La consommation totale d'énergie est influencée par ces mêmes paramètres, mais aussi par la consommation d'eau chaude. Une basse température de consigne pour le système de chauffage combinée à une faible utilisation des appareils électriques mène à des environnements intérieurs trop froids pour être confortables. D'un autre côté, surconsommer de l'électricité peut être néfaste en termes de confort thermique puisque la chaleur générée par les appareils électroniques engendre de la surchauffe. Par rapport aux aspects comportementaux, l'orientation n'a pas d'influence significative sur la consommation énergétique d'un logement et le confort thermique qu'il offre à ses occupants. Il en va de même pour la quantité de masse thermique dans l'enveloppe du logement. Ce dernier point contredit ce qui est observé avec les mesures des *Habitations Trentino*, où l'ajout de masse thermique semblait provoquer plus de surchauffe durant l'été.

Les résultats obtenus suggèrent également que la considération de la diversité des comportements des occupants peut améliorer le dimensionnement des systèmes mécaniques. À titre d'exemple, une nouvelle méthodologie de dimensionnement des systèmes d'eau chaude pour un bâtiment multirésidentiel est proposée dans la thèse. Le dimensionnement d'un système à eau chaude repose sur le volume de réservoir disponible d'eau chaude et sur la puissance nominale du système pour chauffer l'eau. La méthodologie présentée emploie des profils de consommation d'eau chaude générés par l'outil centralisateur du comportement des occupants pour identifier des combinaisons optimales de ces deux variables. Une combinaison est considérée comme étant optimale si elle minimise les dimensions du système tout en s'assurant qu'il n'y a jamais un manque d'eau chaude lorsque les occupants en demandent. En appliquant cette nouvelle méthodologie aux *Habitations Trentino* (le système actuel est basé sur les règles de l'art de l'industrie), on remarque que le système aurait pu être considérablement plus petit. Ce constat montre l'amélioration potentielle de la performance énergétique des systèmes mécaniques de bâtiment qu'on peut obtenir en haussant le niveau de précision de la représentation des occupants.

Travaux futurs

Cette thèse a dégagé plusieurs points pouvant orienter les futures recherches portant sur les bâtiments résidentiels à faible consommation énergétique. Nous pouvons par exemple penser au fait que la part de la demande en chauffage dans la répartition énergétique des bâtiments résidentiels diminue au fur et à mesure qu'on améliore leur conception tel que montré par *Les Habitations Trentino*. Il faudra dans le futur éviter de se concentrer uniquement sur la demande en chauffage et mettre plus d'efforts sur l'augmentation de l'efficacité des systèmes à eau chaude et des appareils électriques pour améliorer davantage les bâtiments.

Les Habitations Trentino sont un exemple frappant du grand impact que les occupants peuvent avoir sur la performance énergétique d'un bâtiment résidentiel. Comme il a été montré dans cette thèse, il est utile pour les concepteurs de bâtiments de se doter d'une méthodologie représentant fidèlement l'aspect probabiliste du comportement des occupants. Pour ce faire, il faut bien comprendre les divers facteurs d'influence affectant le comportement des gens à domicile. L'outil simulant le comportement des occupants développé dans cette thèse peut être amélioré en considérant plus de variables (âge et genre des occupants, statut socio-économique…). Durant le Chapitre 4, une hypothèse est émise comme quoi le fait que *Les Habitations Trentino* contient des logements sociaux habités par de nombreuses jeunes familles puisse expliquer les différences entre les prédictions de l'outil et ce qui est réellement observé. Le modèle pourrait potentiellement être amélioré en utilisant de telles variables, mais cela requiert davantage de recherches et de données. Il faut aussi s'assurer d'avoir un bon équilibre entre la simplicité d'utilisation et la précision d'un modèle d'occupants.

La minimisation de la dépendance énergétique des bâtiments implique une certaine optimisation du comportement des occupants étant donné leur rôle majeur. Cela soulève la question de comment orienter les gens vers un comportement efficace en termes de consommation énergétique et de confort thermique sans brimer sur leurs libertés. Les recherches effectuées en ce moment sur la sensibilisation et la formation des occupants pour les guider vers un comportement énergétiquement efficace sont importantes et devront être accentuées. Aujourd'hui, avec l'avènement des bâtiments intelligents et des téléphones cellulaires, une application permettant une certaine rétroaction sur l'effet énergétique des différents gestes posés par les gens à la maison a un grand potentiel. Il faut s'assurer de la grande efficacité de tels programmes.

Les différents modèles statistiques développés dans le cadre de cette thèse montrent qu'il est possible de prédire avec justesse la charge de chauffage et la température intérieure de logements avec des modèles de régression linéaire. Dans cette thèse, ces modèles ont été employés seulement pour quantifier l'impact des différents prédicteurs considérées. Étant donné leur relative simplicité, il serait intéressant de voir le potentiel de tels modèles lorsqu'employés dans une certaine stratégie de contrôle prédictif. Le modèle se fierait sur les prévisions météorologiques et ses propres prédictions du comportement futur des occupants pour estimer à l'avance les demandes en chauffage ou en climatisation d'un bâtiment résidentiel. Selon ses prévisions, le contrôleur prendrait la décision optimale qui minimiserait la consommation énergétique et l'inconfort des occupants. Le modèle de régression s'auto-calibrerait jour après jour pour s'assurer de suivre le comportement thermique du bâtiment.

Un des objectifs de cette thèse était de comparer la performance énergétique d'appartements avec une structure légère de bois à celle d'appartements employant du CLT. Les résultats in-situ et numériques à ce sujet sont quelque peu contradictoires dans le sens que les mesures suggèrent que le CLT amène plus de surchauffe en été alors que les simulations remarquent aucune distinction entre les deux types de structures. Cette contradiction s'explique peut-être par la différence de l'orientation et de l'ombrage des deux blocs du bâtiment étudié. Néanmoins, des recherches plus approfondies sur la comparaison entre les deux types d'enveloppe seraient intéressantes. L'étude des profils hygrothermiques à travers les deux types d'enveloppe seraient utiles pour entrevoir les transferts de chaleur et de masse qui se produisent au sein de ceux-ci. Dans tous les cas, les mesures et les simulations s'entendent pour dire qu'il n'y a pas de différences notables pour la demande en chauffage entre l'ossature légère et le CLT.

References

[1] US EPA Office of Policy, Economics, and Innovation, “Buildings and their impact on the environment: a statistical summary.” 2009.

[2] Global Alliance for Buildings and Construction, “Global status report 2017.” 2017.

[3] American Society of Heating, Refrigerating and Air-Conditioning Engineers, “ASHRAE Vision 2020 - Providing tools by 2020 that enable the building community to produce market-viable NZEBs by 2030,” ASHRAE, Atlanta, GA, Jan. 2008.

[4] Electricity Reliability Council of Texas, “Long-term hourly peak demand and energy forecast (ERCOT).” 2013.

[5] M. Krarti and K. Dubey, “Benefits of energy efficiency programs for residential buildings in Bahrain,” *J. Build. Eng.*, vol. 18, pp. 40–50, Jul. 2018.

[6] Hydro-Québec, “Consommation d’électricité par grand froid,” *Hydro-Québec*, 2018. [Online]. Available: http://www.hydroquebec.com/residentiel/espace-clients/consommation/consommation-electrique-hiver.html.

[7] B. Bordass, R. Cohen, and J. Field, “Energy performance of non-domestic buildings: closing the credibility gap,” presented at the Building performance congress, 2004.

[8] P. de Wilde, “The gap between predicted and measured energy performance of buildings: A framework for investigation,” *Autom. Constr.*, vol. 41, pp. 40–49, May 2014.

[9] C. Demanuele, T. Tweddell, and M. Davies, “Bridging the gap between predicted and actual energy performance in schools,” presented at the World renewable energy congress XI, Abu Dhabi, UAE, 2010.

[10] C. van Dronkelaar, M. Dowson, E. Burman, C. Spataru, and D. Mumovic, “A Review of the Energy Performance Gap and Its Underlying Causes in Non-Domestic Buildings,” *Front. Mech. Eng.*, vol. 1, 2016.

[11] L. Tronchin and K. Fabbri, “Energy performance building evaluation in Mediterranean countries: Comparison between software simulations and operating rating simulation,” *Energy Build.*, vol. 40, no. 7, pp. 1176–1187, 2008.

[12] R. V. Jones, A. Fuertes, and P. de Wilde, “The gap between simulated and measured energy performance: a case study across six identical new-build flats in the UK,” presented at the 14th Conference of International Building Performance Simulation Association, Hyderabad, India, 2015.

[13] D. Calì, T. Osterhage, R. Streblow, and D. Müller, “Energy performance gap in refurbished German dwellings: Lesson learned from a field test,” *Energy Build.*, vol. 127, pp. 1146–1158, Sep. 2016.

[14] G. Dall’O’, L. Sarto, N. Sanna, and A. Martucci, “Comparison between predicted and actual energy performance for summer cooling in high-performance residential buildings in the Lombardy region (Italy),” *Energy Build.*, vol. 54, pp. 234–242, Nov. 2012.

[15] G. Dall’O’, L. Sarto, A. Galante, and G. Pasetti, “Comparison between predicted and actual energy performance for winter heating in high-performance residential buildings in the Lombardy region (Italy),” *Energy Build.*, vol. 47, pp. 247–253, Apr. 2012.

[16] P. Hoes, J. L. M. Hensen, M. G. L. C. Loomans, B. de Vries, and D. Bourgeois, “User behavior in whole building simulation,” *Energy Build.*, vol. 41, no. 3, pp. 295–302, Mar. 2009.

[17] A. Ioannou and L. C. M. Itard, “Energy performance and comfort in residential buildings: Sensitivity for building parameters and occupancy,” *Energy Build.*, vol. 92, pp. 216–233, Apr. 2015.
[18] A. F. Emery and C. J. Kippenhan, “A long term study of residential home heating consumption and the effect of occupant behavior on homes in the Pacific Northwest constructed according to improved thermal standards,” *Energy*, vol. 31, no. 5, pp. 677–693, Apr. 2006.
[19] J. Virote and R. Neves-Silva, “Stochastic models for building energy prediction based on occupant behavior assessment,” *Energy Build.*, vol. 53, pp. 183–193, Oct. 2012.
[20] US EIA, “Annual energy review - Energy consumption by sector,” 2013. [Online]. Available: https://www.eia.gov/totalenergy/data/annual/#consumption.
[21] Official Journal of the European Union, “Directive 2010/31/EU of the European Parliament and of the Council of 19 May 2010 on the energy performance of buildings,” 2010.
[22] American Society of Heating, Refrigerating and Air-Conditioning Engineers, “ASHRAE Vision 2020 - Providing tools by 2020 that enable the building community to produce market-viable NZEBs by 2030,” ASHRAE, Atlanta, GA, Jan. 2008.
[23] European Performance of Buildings Directive, “Towards nearly zero-energy buildings - Definition of common principles under the EPBD,” EPBD, Köln, Germany, Feb. 2013.
[24] A. F. Emery and C. J. Kippenhan, “A long term study of residential home heating consumption and the effect of occupant behavior on homes in the Pacific Northwest constructed according to improved thermal standards,” *Energy*, vol. 31, no. 5, pp. 677–693, Apr. 2006.
[25] M. R. Braun, H. Altan, and S. B. M. Beck, “Using regression analysis to predict the future energy consumption of a supermarket in the UK,” *Appl. Energy*, vol. 130, pp. 305–313, Oct. 2014.
[26] T. Catalina, J. Virgone, and E. Blanco, “Development and validation of regression models to predict monthly heating demand for residential buildings,” *Energy Build.*, vol. 40, no. 10, pp. 1825–1832, 2008.
[27] B. Soldo, P. Potočnik, G. Šimunović, T. Šarić, and E. Govekar, “Improving the residential natural gas consumption forecasting models by using solar radiation,” *Energy Build.*, vol. 69, pp. 498–506, Feb. 2014.
[28] N. Fumo and M. A. Rafe Biswas, “Regression analysis for prediction of residential energy consumption,” *Renew. Sustain. Energy Rev.*, vol. 47, pp. 332–343, Jul. 2015.
[29] S. S. Amiri, M. Mottahedi, and S. Asadi, “Using multiple regression analysis to develop energy consumption indicators for commercial buildings in the U.S.,” *Energy Build.*, vol. 109, pp. 209–216, Dec. 2015.
[30] S. Asadi, S. S. Amiri, and M. Mottahedi, “On the development of multi-linear regression analysis to assess energy consumption in the early stages of building design,” *Energy Build.*, vol. 85, pp. 246–255, Dec. 2014.
[31] M. Mottahedi, A. Mohammadpour, S. S. Amiri, D. Riley, and S. Asadi, “Multi-linear Regression Models to Predict the Annual Energy Consumption of an Office Building with Different Shapes,” *Procedia Eng.*, vol. 118, pp. 622–629, Jan. 2015.
[32] J. Kneifel and D. Webb, “Predicting energy performance of a net-zero energy building: A statistical approach,” *Appl. Energy*, vol. 178, pp. 468–483, Sep. 2016.

[33] J. Chen, X. Wang, and K. Steemers, “A statistical analysis of a residential energy consumption survey study in Hangzhou, China,” *Energy Build.*, vol. 66, pp. 193–202, Nov. 2013.
[34] B. Bordass, R. Cohen, and J. Field, “Energy perfromance of non-domestic buildings: closing the credibility gap,” presented at the International conference on improving energy efficiency in commercial buildings, Frankfurt, Germany, 2004.
[35] C. Demanuele, T. Tweddell, and M. Davies, “Bridging the gap between predicted and actual energy performance in schools,” presented at the World renewable energy congress XI, Abu Dhabi, UAE, 2010.
[36] I. Danielski, “Large variations in specific final energy use in Swedish apartment buildings: Causes and solutions,” *Energy Build.*, vol. 49, pp. 276–285, Jun. 2012.
[37] P. de Wilde, “The gap between predicted and measured energy performance of buildings: A framework for investigation,” *Autom. Constr.*, vol. 41, pp. 40–49, May 2014.
[38] L. Tronchin and K. Fabbri, “Energy performance building evaluation in Mediterranean countries: Comparison between software simulations and operating rating simulation,” *Energy Build.*, vol. 40, no. 7, pp. 1176–1187, 2008.
[39] R. V. Jones, A. Fuertes, and P. de Wilde, “The gap between simulated and measured energy performance: a case study across six identical new-build flats in the UK,” presented at the 14th Conference of International Building Performance Simulation Association, Hyderabad, India, 2015.
[40] S. Imam, D. A. Coley, and I. Walker, “The building performance gap: Are modellers literate?,” *Build. Serv. Eng. Res. Technol.*, vol. 38, no. 3, pp. 351–375, May 2017.
[41] C. Yu, W. Pan, Y. Zhao, and Y. Li, “Challenges for Modeling Energy Use in High-rise Office Buildings in Hong Kong,” *Procedia Eng.*, vol. 121, pp. 513–520, Jan. 2015.
[42] Z. O’Neill and F. Niu, “Uncertainty and sensitivity analysis of spatio-temporal occupant behaviors on residential building energy usage utilizing Karhunen-Loève expansion,” *Build. Environ.*, vol. 115, no. Supplement C, pp. 157–172, Apr. 2017.
[43] P. H. Fabriek, “Sensitivity analysis of residential building simulations: Model choice for specific applications and critical parameters,” TU Delft, Delft University of Technology, 2013.
[44] N. Delgarm, B. Sajadi, K. Azarbad, and S. Delgarm, “Sensitivity analysis of building energy performance: A simulation-based approach using OFAT and variance-based sensitivity analysis methods,” *J. Build. Eng.*, vol. 15, pp. 181–193, Jan. 2018.
[45] R. Ghedamsi *et al.*, “Modeling and forecasting energy consumption for residential buildings in Algeria using bottom-up approach,” *Energy Build.*, vol. 121, no. Supplement C, pp. 309–317, Jun. 2016.
[46] D. Liu, W. Wang, and J. Liu, “Sensitivity Analysis of Meteorological Parameters on Building Energy Consumption,” *Energy Procedia*, vol. 132, no. Supplement C, pp. 634–639, Oct. 2017.
[47] T. S. Blight and D. A. Coley, “Sensitivity analysis of the effect of occupant behaviour on the energy consumption of passive house dwellings,” *Energy Build.*, vol. 66, pp. 183–192, Nov. 2013.
[48] S. M. C. Magalhães, V. M. S. Leal, and I. M. Horta, “Modelling the relationship between heating energy use and indoor temperatures in residential buildings through Artificial Neural Networks considering occupant behavior,” *Energy Build.*, vol. 151, no. Supplement C, pp. 332–343, Sep. 2017.

[49] L. Diao, Y. Sun, Z. Chen, and J. Chen, "Modeling energy consumption in residential buildings: A bottom-up analysis based on occupant behavior pattern clustering and stochastic simulation," *Energy Build.*, vol. 147, no. Supplement C, pp. 47–66, Jul. 2017.
[50] D. Calì, T. Osterhage, R. Streblow, and D. Müller, "Energy performance gap in refurbished German dwellings: Lesson learned from a field test," *Energy Build.*, vol. 127, pp. 1146–1158, Sep. 2016.
[51] G. Dall'O', L. Sarto, A. Galante, and G. Pasetti, "Comparison between predicted and actual energy performance for winter heating in high-performance residential buildings in the Lombardy region (Italy)," *Energy Build.*, vol. 47, pp. 247–253, Apr. 2012.
[52] G. Dall'O', L. Sarto, N. Sanna, and A. Martucci, "Comparison between predicted and actual energy performance for summer cooling in high-performance residential buildings in the Lombardy region (Italy)," *Energy Build.*, vol. 54, pp. 234–242, Nov. 2012.
[53] Statistics Canada, "Census profile - 2016 Census," 2016. [Online]. Available: http://www12.statcan.gc.ca/census-recensement/2016/dp-pd/prof/index.cfm?Lang=E.
[54] J. Schmidt and C. Griffin, "Barriers to the design and use of cross-laminated timber structures in high-rise multi-family housing in the United States," in *Structures and Architecture*, 0 vols., CRC Press, 2013, pp. 2225–2231.
[55] W. Feist, *PHPP - Passive House Planning Package*. Passive House Institute, 2012.
[56] C. J. Hopfe and R. S. McLeod, *The Passivhaus Designer's Manual: A Technical Guide to Low and Zero Energy Buildings*. Routledge, 2015.
[57] Sontex, "Compact thermal Energy Meter - Data sheet." 2013.
[58] Delta controls, "Network sensors - BACstat II: DNS-x24." 2011.
[59] Campbell Scientific, "Instruction manual - 44212 and 44212EC temperature probes." Dec-2014.
[60] Vaisala, "User guide - Vaisala HUMICAP Humidity and temperature probes - HMP4." 2017.
[61] R.M. Young company, "Model 05103 Wind Monitor." 2005.
[62] Xylem Inc., "WE300 Solar radiation sensor," 2015. [Online]. Available: http://www.globalw.com/products/we300.html.
[63] OTT Hydromet, "OTT Pluvio2 - Weighing rain gauge," 2017. [Online]. Available: http://www.ott.com/en-us/products/accessories-109/ott-pluvio2-weighing-rain-gauge-963/.
[64] National Resources Canada, "Survey of house energy use - Detailed statistical report," Ottawa, 978-1-100-23468–7, 2011.
[65] F. C. McQuiston, J. D. Parker, and J. D. Spitler, *Heating, ventilating, and air conditioning - Analysis and design*, Sixth edition. John Wiley & Sons, 2005.
[66] K. Lee, H.-J. Baek, and C. Cho, "The Estimation of Base Temperature for Heating and Cooling Degree-Days for South Korea," *J. Appl. Meteorol. Climatol.*, vol. 53, no. 2, pp. 300–309, Sep. 2013.
[67] Natural Resources Canada, "Water Heater Guide." Oct-2012.
[68] D. George, N. S. Pearre, and L. G. Swan, "High resolution measured domestic hot water consumption of Canadian homes," *Energy Build.*, vol. 109, pp. 304–315, Dec. 2015.
[69] ASHRAE, "Service Water Heating," in *ASHRAE Handbook - HVAC Applications*, Atlanta, GA, 2015.
[70] J. Whitmore and P.-O. Pineau, "État de l'énergie au Québec 2016," Chaire de gestion du secteur de l'énergie, Montréal, 2015.

[71] D. C. Montgomery, E. A. Peck, and G. G. Vining, *Introduction to Linear Regression Analysis*, 5 edition. Hoboken, NJ: Wiley, 2012.
[72] A. Saltelli *et al.*, *Global Sensitivity Analysis. The Primer*. Chichester, UK: John Wiley & Sons, Ltd, 2007.
[73] T. A. Reddy, *Applied Data Analysis and Modeling for Energy Engineers and Scientists*. Boston, MA: Springer US, 2011.
[74] Z. Wang, Z. Zhao, B. Lin, Y. Zhu, and Q. Ouyang, "Residential heating energy consumption modeling through a bottom-up approach for China's Hot Summer–Cold Winter climatic region," *Energy Build.*, vol. 109, no. Supplement C, pp. 65–74, Dec. 2015.
[75] J. Langevin, P. L. Gurian, and J. Wen, "Reducing energy consumption in low income public housing: Interviewing residents about energy behaviors," *Appl. Energy*, vol. 102, no. Supplement C, pp. 1358–1370, Feb. 2013.
[76] M. Pritoni, K. Salmon, A. Sanguinetti, J. Morejohn, and M. Modera, "Occupant thermal feedback for improved efficiency in university buildings," *Energy Build.*, vol. 144, no. Supplement C, pp. 241–250, Jun. 2017.
[77] M. Vellei, S. Natarajan, B. Biri, J. Padget, and I. Walker, "The effect of real-time context-aware feedback on occupants' heating behaviour and thermal adaptation," *Energy Build.*, vol. 123, no. Supplement C, pp. 179–191, Jul. 2016.
[78] S. Khashe, G. Lucas, B. Becerik-Gerber, and J. Gratch, "Buildings with persona: Towards effective building-occupant communication," *Comput. Hum. Behav.*, vol. 75, no. Supplement C, pp. 607–618, Oct. 2017.
[79] P. R. Warren and L. M. Parkins, "Single-sided ventilation through open windows," presented at the Windows in building design and maintenance, Goteborg Sweden, 1984, p. 487.
[80] D. Hémon and E. Jougla, "Surmortalité liée à la canicule d'août 2003," Institut national de la santé et de la recherche médicale, Paris, France, Oct. 2004.
[81] ASHRAE, "ANSI/ASHRAE Standard 55-2013, Thermal environmental conditions for human occupancy," Atlanta, GA, 2017.
[82] Natural Resources Canada, "Comprehensive energy use database tables," 31-Jan-2014. [Online]. Available: http://oee.nrcan.gc.ca/corporate/statistics/neud/dpa/trends_egen_ca.cfm?attr=0.
[83] ASHRAE, "ANSI/ASHRAE Standard 62.2-2016, Ventilation and acceptable indoor air quality in residential buildings," Atlanta, GA, 2016.
[84] IEA International Energy Agency, "Energy technology perspectives 2016 - Towards sustainable urban energy systems," Paris, 2016.
[85] A. F. Emery and C. J. Kippenhan, "A long term study of residential home heating consumption and the effect of occupant behavior on homes in the Pacific Northwest constructed according to improved thermal standards," *Energy*, vol. 31, no. 5, pp. 677–693, Apr. 2006.
[86] B. Boardman, "Home truths: a low-carbon strategy to reduce UK housing emissions by 80% by 2050," University of Oxfords' Environmental Change Institute, Nov. 2007.
[87] P. de Wilde and D. Coley, "The implications of a changing climate for buildings," *Build. Environ.*, vol. 55, pp. 1–7, Sep. 2012.
[88] V. Fabi, R. V. Andersen, S. Corgnati, and B. W. Olesen, "Occupants' window opening behaviour: A literature review of factors influencing occupant behaviour and models," *Build. Environ.*, vol. 58, pp. 188–198, Dec. 2012.

[89] S. A. Sadeghi, P. Karava, I. Konstantzos, and A. Tzempelikos, “Occupant interactions with shading and lighting systems using different control interfaces: A pilot field study,” *Build. Environ.*, vol. 97, pp. 177–195, Feb. 2016.
[90] M. Schweiker and M. Shukuya, “Comparison of theoretical and statistical models of air-conditioning-unit usage behaviour in a residential setting under Japanese climatic conditions,” *Build. Environ.*, vol. 44, no. 10, pp. 2137–2149, Oct. 2009.
[91] P. Hoes, J. L. M. Hensen, M. G. L. C. Loomans, B. de Vries, and D. Bourgeois, “User behavior in whole building simulation,” *Energy Build.*, vol. 41, no. 3, pp. 295–302, Mar. 2009.
[92] D. Yan *et al.*, “Occupant behavior modeling for building performance simulation: Current state and future challenges,” *Energy Build.*, vol. 107, pp. 264–278, Nov. 2015.
[93] B. Bordass, R. Cohen, and J. Field, “Energy performance of non-domestic buildings: closing the credibility gap,” presented at the Building performance congress, 2004.
[94] J. Widén and E. Wäckelgård, “A high-resolution stochastic model of domestic activity patterns and electricity demand,” *Appl. Energy*, vol. 87, no. 6, pp. 1880–1892, Jun. 2010.
[95] M. Schweiker, F. Haldi, M. Shukuya, and D. Robinson, “Verification of stochastic models of window opening behaviour for residential buildings,” *J. Build. Perform. Simul.*, vol. 5, no. 1, pp. 55–74, Jan. 2012.
[96] U. Wilke, F. Haldi, J.-L. Scartezzini, and D. Robinson, “A bottom-up stochastic model to predict building occupants’ time-dependent activities,” *Build. Environ.*, vol. 60, pp. 254–264, Feb. 2013.
[97] D. Fischer, T. Wolf, J. Scherer, and B. Wille-Haussmann, “A stochastic bottom-up model for space heating and domestic hot water load profiles for German households,” *Energy Build.*, vol. 124, pp. 120–128, Jul. 2016.
[98] A. P. Ramallo-González, T. S. Blight, and D. A. Coley, “New optimisation methodology to uncover robust low energy designs that accounts for occupant behaviour or other unknowns,” *J. Build. Eng.*, vol. 2, pp. 59–68, Jun. 2015.
[99] I. Richardson, M. Thomson, and D. Infield, “A high-resolution domestic building occupancy model for energy demand simulations,” *Energy Build.*, vol. 40, no. 8, pp. 1560–1566, 2008.
[100] R. Hendron, J. Burch, and G. Barker, “Tool for generating realistic residential hot water event schedules,” *Natl. Renew. Energy Lab. Gold. CO Pap. No NRELCP-550-47685*, 2010.
[101] I. Richardson, M. Thomson, D. Infield, and C. Clifford, “Domestic electricity use: A high-resolution energy demand model,” *Energy Build.*, vol. 42, no. 10, pp. 1878–1887, Oct. 2010.
[102] M. Schweiker, M. Hawighorst, and A. Wagner, “The influence of personality traits on occupant behavioural patterns,” *Energy Build.*, vol. 131, pp. 63–75, Nov. 2016.
[103] R. McKenna, L. Hofmann, E. Merkel, W. Fichtner, and N. Strachan, “Analysing socioeconomic diversity and scaling effects on residential electricity load profiles in the context of low carbon technology uptake,” *Energy Policy*, vol. 97, pp. 13–26, Oct. 2016.
[104] Centre for Time Use Research, “Multinational Time Use Study.” [Online]. Available: https://www.timeuse.org/mtus.
[105] Mathworks, *MATLAB*. 2014.
[106] S. Brooks, A. Gelman, G. Jones, and X.-L. Meng, Eds., *Handbook of Markov Chain Monte Carlo*. Boca Raton: Chapman and Hall/CRC, 2011.

[107] Ipsos-RSL and Office for National Statistics, “United Kingdom Time Use Survey, 2000 (Computer file),” UK Data Archive (distributor), Colchester, Essex, Sep. 2003.
[108] Statistics Canada, “Canadian households in 2011: Type and growth,” Catalogue no. 98-312-X2011003, 2011.
[109] M. Muratori, M. C. Roberts, R. Sioshansi, V. Marano, and G. Rizzoni, “A highly resolved modeling technique to simulate residential power demand,” *Appl. Energy*, vol. 107, pp. 465–473, Jul. 2013.
[110] M. A. López-Rodríguez, I. Santiago, D. Trillo-Montero, J. Torriti, and A. Moreno-Munoz, “Analysis and modeling of active occupancy of the residential sector in Spain: An indicator of residential electricity consumption,” *Energy Policy*, vol. 62, pp. 742–751, Nov. 2013.
[111] J. Widén, A. M. Nilsson, and E. Wäckelgård, “A combined Markov-chain and bottom-up approach to modelling of domestic lighting demand,” *Energy Build.*, vol. 41, no. 10, pp. 1001–1012, Oct. 2009.
[112] Statistics Canada, “General Social Survey on Time Use - Overview of the Time Use of Canadians 2005,” Ottawa, Catalogue no. 12F0090XIE, Jul. 2006.
[113] E. McKenna, M. Krawczynski, and M. Thomson, “Four-state domestic building occupancy model for energy demand simulations,” *Energy Build.*, vol. 96, pp. 30–39, Jun. 2015.
[114] D. Aerts, J. Minnen, I. Glorieux, I. Wouters, and F. Descamps, “A method for the identification and modelling of realistic domestic occupancy sequences for building energy demand simulations and peer comparison,” *Build. Environ.*, vol. 75, pp. 67–78, May 2014.
[115] L. Gelažanskas and K. A. A. Gamage, “Forecasting hot water consumption in dwellings using artificial neural networks,” in *2015 IEEE 5th International Conference on Power Engineering, Energy and Electrical Drives (POWERENG)*, 2015, pp. 410–415.
[116] A. Lomet, F. Suard, and D. Chèze, “Statistical Modeling for Real Domestic Hot Water Consumption Forecasting,” *Energy Procedia*, vol. 70, pp. 379–387, May 2015.
[117] C. Sandels, J. Widén, and L. Nordström, “Forecasting household consumer electricity load profiles with a combined physical and behavioral approach,” *Appl. Energy*, vol. 131, pp. 267–278, Oct. 2014.
[118] J. Widén, M. Lundh, I. Vassileva, E. Dahlquist, K. Ellegård, and E. Wäckelgård, “Constructing load profiles for household electricity and hot water from time-use data—Modelling approach and validation,” *Energy Build.*, vol. 41, no. 7, pp. 753–768, Jul. 2009.
[119] D. Popescu and E. Serban, “Simulation of domestic hot-water consumption using time-series models,” presented at the 6th IASME/WSEAS International Conference on Heat Transer, Thermal Engineering and Environment, Rhodes, Greece, 2008.
[120] V. Bakker, A. Molderink, J. L. Hurink, and G. J. M. Smit, “Domestic Heat Demand Prediction Using Neural Networks,” in *2008 19th International Conference on Systems Engineering*, 2008, pp. 189–194.
[121] R. Hendron and C. Engrebrecht, “Building America Research Benchmark Definition,” NREL, Golden, CO, TP-550-47246, Dec. 2009.
[122] Natural Resources Canada, *HOT2000*. Ottawa, 2016.

[123] K. Adye, N. S. Pearre, and L. G. Swan, “On-site Assessment Summary Report: House Characteristics and Water and Energy Savings,” Halifax Regional Municipality, Halifax, 2014.
[124] D. S. Parker and P. Fairey, “Estimating Daily Domestic Hot-Water Use in North American Homes,” *ASHRAE Trans.*, vol. 121, p. 258, 2015.
[125] M. Chitnis and L. C. Hunt, “Modelling UK household expenditure: economic versus noneconomic drivers,” *Appl. Econ. Lett.*, vol. 18, no. 8, pp. 753–767, Jun. 2011.
[126] J. L. Harris and L.-M. Liu, “Dynamic structural analysis and forecasting of residential electricity consumption,” *Int. J. Forecast.*, vol. 9, no. 4, pp. 437–455, Dec. 1993.
[127] D. Fischer, A. Härtl, and B. Wille-Haussmann, “Model for electric load profiles with high time resolution for German households,” *Energy Build.*, vol. 92, pp. 170–179, Apr. 2015.
[128] A. Capasso, W. Grattieri, R. Lamedica, and A. Prudenzi, “A bottom-up approach to residential load modeling,” *IEEE Trans. Power Syst.*, vol. 9, no. 2, pp. 957–964, May 1994.
[129] R. Baetens *et al.*, “Assessing electrical bottlenecks at feeder level for residential net zero-energy buildings by integrated system simulation,” *Appl. Energy*, vol. 96, pp. 74–83, Aug. 2012.
[130] A. Marszal-Pomianowska, P. Heiselberg, and O. Kalyanova Larsen, “Household electricity demand profiles – A high-resolution load model to facilitate modelling of energy flexible buildings,” *Energy*, vol. 103, pp. 487–501, May 2016.
[131] M. M. Armstrong, M. C. Swinton, H. Ribberink, I. Beausoleil-Morrison, and J. Millette, “Synthetically derived profiles for representing occupant-driven electric loads in Canadian housing,” *J. Build. Perform. Simul.*, vol. 2, no. 1, pp. 15–30, Mar. 2009.
[132] R. Subbiah, “An activity-based energy demand modeling framework for buildings: A bottom-up approach,” Thesis, Virginia Tech, 2013.
[133] Statistics Canada, “Households and the environment: Energy use,” Ottawa, 1920–7522, Apr. 2010.
[134] Energy saving trust, “Measurement of Domestic Hot Water Consumption in Dwellings,” 2008.
[135] D. George, “New profiles of occupancy driven appliance, lighting, plug loads and hot water use for residenial sector energy demand modeling,” Dalhousie University, Halifax, Nova Scotia, 2016.
[136] D. Godoy-Shimizu, J. Palmer, and N. Terry, “What Can We Learn from the Household Electricity Survey?,” *Buildings*, vol. 4, no. 4, pp. 737–761, Oct. 2014.
[137] F. M. Andersen, M. Baldini, L. G. Hansen, and C. L. Jensen, “Households’ hourly electricity consumption and peak demand in Denmark,” *Appl. Energy*, vol. 208, pp. 607–619, Dec. 2017.
[138] B. R. Becker, W. H. Thrasher, and D. W. DeWerth, “Comparison of collected and compiled existing data on service hot water use patterns in residential and commercial establishments,” *ASHRAE Trans.*, vol. 97, no. 2, pp. 231–239, 1991.
[139] F. S. Goldner, “Energy use and domestic hot water consumption: Final report - Phase 1,” New York State Energy Research and Development Authority, Albany, NY, 94–19, 1994.
[140] F. S. Goldner, “DHW system sizing criteria for multifamily buildings,” *ASHRAE Trans.*, vol. 100, no. 1, pp. 963–977, 1994.

[141] F. S. Goldner and D. C. Price, “DHW modeling: System sizing and selection criteria, Phase 2,” New York State Energy Research and Development Authority, Albany, NY, Interim Project Research Report 1, 1996.
[142] ASHRAE, “Energy Standard for Buildings Except Low-Rise Residential Buildings,” Atlanta: ASHRAE, 2016.
[143] The University of Wisconsin Madison, *TRNSYS 17 - A Transient Systems Simulation Program*. 2013.
[144] H. Hens, W. Parijs, and M. Deurinck, “Energy consumption for heating and rebound effects,” *Energy Build.*, vol. 42, no. 1, pp. 105–110, Jan. 2010.
[145] T. Hong, D. Yan, S. D’Oca, and C. Chen, “Ten questions concerning occupant behavior in buildings: The big picture,” *Build. Environ.*, vol. 114, pp. 518–530, Mar. 2017.
[146] B. Gucyeter, “Evaluating diverse patterns of occupant behavior regarding control-based activities in energy performance simulation,” *Front. Archit. Res.*, Apr. 2018.
[147] J. Kim, Y. Zhou, S. Schiavon, P. Raftery, and G. Brager, “Personal comfort models: Predicting individuals’ thermal preference using occupant heating and cooling behavior and machine learning,” *Build. Environ.*, vol. 129, pp. 96–106, Feb. 2018.
[148] S. Gilani, W. O’Brien, and H. B. Gunay, “Simulating occupants’ impact on building energy performance at different spatial scales,” *Build. Environ.*, vol. 132, pp. 327–337, Mar. 2018.
[149] U. Jordan and K. Vajen, “Influence Of The DHW Load Profile On The Fractional Energy Savings:: A Case Study Of A Solar Combi-System With TRNSYS Simulations,” *Sol. Energy*, vol. 69, Supplement 6, pp. 197–208, Jul. 2001.
[150] F. Haldi, D. Calì, R. K. Andersen, M. Wesseling, and D. Müller, “Modelling diversity in building occupant behaviour: a novel statistical approach,” *J. Build. Perform. Simul.*, vol. 10, no. 5–6, pp. 527–544, Nov. 2017.
[151] Y. He, N. Li, N. Li, J. Li, J. Yan, and C. Tan, “Control behaviors and thermal comfort in a shared room with desk fans and adjustable thermostat,” *Build. Environ.*, vol. 136, pp. 213–226, May 2018.
[152] F. Haldi and D. Robinson, “Adaptive actions on shading devices in response to local visual stimuli,” *J. Build. Perform. Simul.*, vol. 3, no. 2, pp. 135–153, Jun. 2010.
[153] Z. M. Gill, M. J. Tierney, I. M. Pegg, and N. Allan, “Low-energy dwellings: the contribution of behaviours to actual performance,” *Build. Res. Inf.*, vol. 38, no. 5, pp. 491–508, Oct. 2010.
[154] F. Haldi and D. Robinson, “The impact of occupants’ behaviour on building energy demand,” *J. Build. Perform. Simul.*, vol. 4, no. 4, pp. 323–338, Dec. 2011.
[155] S. Karjalainen, “Should we design buildings that are less sensitive to occupant behaviour? A simulation study of effects of behaviour and design on office energy consumption,” *Energy Effic.*, vol. 9, no. 6, pp. 1257–1270, Dec. 2016.
[156] T. de Meester, A.-F. Marique, A. De Herde, and S. Reiter, “Impacts of occupant behaviours on residential heating consumption for detached houses in a temperate climate in the northern part of Europe,” *Energy Build.*, vol. 57, pp. 313–323, Feb. 2013.
[157] H. B. Gunay, W. O’Brien, I. Beausoleil-Morrison, R. Goldstein, S. Breslav, and A. Khan, “Coupling stochastic occupant models to building performance simulation using the discrete event system specification formalism,” *J. Build. Perform. Simul.*, vol. 7, no. 6, pp. 457–478, Nov. 2014.

[158] E. Delzendeh, S. Wu, A. Lee, and Y. Zhou, “The impact of occupants’ behaviours on building energy analysis: A research review,” *Renew. Sustain. Energy Rev.*, vol. 80, pp. 1061–1071, Dec. 2017.
[159] E. McKenna and M. Thomson, “High-resolution stochastic integrated thermal–electrical domestic demand model,” *Appl. Energy*, vol. 165, pp. 445–461, Mar. 2016.
[160] F. Haldi and D. Robinson, “Interactions with window openings by office occupants,” *Build. Environ.*, vol. 44, no. 12, pp. 2378–2395, Dec. 2009.
[161] R. Kotireddy, P.-J. Hoes, and J. L. M. Hensen, “A methodology for performance robustness assessment of low-energy buildings using scenario analysis,” *Appl. Energy*, vol. 212, pp. 428–442, Feb. 2018.
[162] J. Kneifel, W. Healy, J. Filliben, and M. Boyd, “Energy performance sensitivity of a net-zero energy home to design and use specifications,” *J. Build. Perform. Simul.*, vol. 9, no. 1, pp. 70–83, Jan. 2016.
[163] F. R. Cecconi, M. Manfren, L. C. Tagliabue, A. L. C. Ciribini, and E. De Angelis, “Probabilistic behavioral modeling in building performance simulation: A Monte Carlo approach,” *Energy Build.*, vol. 148, pp. 128–141, Aug. 2017.
[164] M. J. Bordbari, A. R. Seifi, and M. Rastegar, “Probabilistic energy consumption analysis in buildings using point estimate method,” *Energy*, vol. 142, pp. 716–722, Jan. 2018.
[165] I. Gaetani, P.-J. Hoes, and J. L. M. Hensen, “On the sensitivity to different aspects of occupant behaviour for selecting the appropriate modelling complexity in building performance predictions,” *J. Build. Perform. Simul.*, vol. 10, no. 5–6, pp. 601–611, Nov. 2017.
[166] T. Buso, V. Fabi, R. K. Andersen, and S. P. Corgnati, “Occupant behaviour and robustness of building design,” *Build. Environ.*, vol. 94, pp. 694–703, Dec. 2015.
[167] Office of Energy Efficiency, “Table 33 - Gross output thermal requirements per square metre by building type and vintage - Residential sector - Quebec,” *Natural Resources Canada*. [Online]. Available: http://oee.rncan.gc.ca/corporate/statistics/neud/dpa/showTable.cfm?type=CP&sector=res&juris=qc&rn=33&page=4.
[168] Omega Engineering, “SA1-RTD-B series specs sheet.” .
[169] Sontex, “Compact thermal Energy Meter - Data sheet.” 2013.
[170] Smart Home Products, “GRI-20RS-12XWG.” 2018.
[171] The University of Wisconsin Madison, *TRNSYS 17 - A Transient Systems Simulation Program*. 2013.
[172] Enerconcept Technologies inc., “Collecteur Lubi transparent - Manuel technique.” Jul-2013.
[173] P. R. Warren, “Ventilation through openings on one wall only,” presented at the Conference Proceedings, Energy conservation in Heating, Cooling and Ventilating, Dubrovnik, Yugoslavia, 1977, vol. 1.
[174] B. Delcroix, M. Kummert, A. Daoud, and M. Hiller, “Conduction transfer functions in TRNSYS multizone building model - Current implementation, limitations and possible improvments,” presented at the SimBuild 2012, Madison, USA, 2012, pp. 219–226.
[175] American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE), “ANSI/ASHRAE Standard 55-2013, Thermal environmental conditions for human occupancy,” Atlanta, GA, 2017.

[176] Y. Song *et al.*, “Residential adaptive comfort in a humid continental climate – Tianjin China,” *Energy Build.*, vol. 170, pp. 115–121, Jul. 2018.
[177] Berkeley Lab, *GenOpt - Generic Optimization Program*. 2016.
[178] P. Penna, F. Cappelletti, A. Gasparella, F. Tahmasebi, and A. Mahdavi, “Multi-stage calibration of the simulation model of a school building through short-term monitoring,” *J. Inf. Technol. Constr.*, vol. 20, pp. 132–145, Jan. 2015.
[179] E. Carlon *et al.*, “On-site monitoring and dynamic simulation of a low energy house heated by a pellet boiler,” *Energy Build.*, vol. 116, pp. 296–306, Mar. 2016.
[180] A. Cacabelos, P. Eguía, J. L. Míguez, E. Granada, and M. E. Arce, “Calibrated simulation of a public library HVAC system with a ground-source heat pump and a radiant floor using TRNSYS and GenOpt,” *Energy Build.*, vol. 108, pp. 114–126, Dec. 2015.
[181] ASHRAE, “Guideline 14-2002: Measurement of energy and demand savings,” American Society of Heating, Refrigerating and Air-Conditioning Engineers, Atlanta, GA, 2002.
[182] American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE), “Guideline 14-2014: Measurement of energy and demand savings,” American Society of Heating, Refrigerating and Air-Conditioning Engineers, Atlanta, GA, Technical Report, 2002.
[183] G. R. Ruiz and C. F. Bandera, “Validation of Calibrated Energy Models: Common Errors,” *Energies*, vol. 10, no. 10, p. 1587, Oct. 2017.
[184] W. O’Brien, H. B. Gunay, F. Tahmasebi, and A. Mahdavi, “A preliminary study of representing the inter-occupant diversity in occupant modelling,” *J. Build. Perform. Simul.*, vol. 10, no. 5–6, pp. 509–526, Nov. 2017.
[185] H. B. Rijal, P. Tuohy, F. Nicol, M. A. Humphreys, A. Samuel, and J. Clarke, “Development of an adaptive window-opening algorithm to predict the thermal comfort, energy use and overheating in buildings,” *J. Build. Perform. Simul.*, vol. 1, no. 1, pp. 17–30, Mar. 2008.
[186] S. Shi and B. Zhao, “Occupants’ interactions with windows in 8 residential apartments in Beijing and Nanjing, China,” *Build. Simul.*, vol. 9, no. 2, pp. 221–231, Dec. 2015.
[187] V. Fabi, R. V. Andersen, S. Corgnati, and B. W. Olesen, “Occupants’ window opening behaviour: A literature review of factors influencing occupant behaviour and models,” *Build. Environ.*, vol. 58, pp. 188–198, Dec. 2012.
[188] F. Haldi, D. Calì, R. K. Andersen, M. Wesseling, and D. Müller, “Modelling diversity in building occupant behaviour: a novel statistical approach,” *J. Build. Perform. Simul.*, vol. 10, no. 5–6, pp. 527–544, Nov. 2017.
[189] American Society of Heating, Refrigerating and Air-Conditioning Engineers, “Appendix G - Building Performance Rating Method - ASHRAE Standard 90.1.” 2004.
[190] D. C. Montgomery, E. A. Peck, and G. G. Vining, *Introduction to Linear Regression Analysis*, 5 edition. Hoboken, NJ: Wiley, 2012.
[191] R. Saidur, H. H. Masjuki, and M. Y. Jamaluddin, “An application of energy and exergy analysis in residential sector of Malaysia,” *Energy Policy*, vol. 35, no. 2, pp. 1050–1063, Feb. 2007.
[192] L. Price, L. Michaelis, E. Worrell, and M. Khrusch, “Sectoral Trends and Driving Forces of Global Energy Use and Greenhouse Gas Emissions,” *Mitig. Adapt. Strateg. Glob. Change*, vol. 3, pp. 263–319, Aug. 1998.

[193] G. Branco, B. Lachal, P. Gallinelli, and W. Weber, “Predicted versus observed heat consumption of a low energy multifamily complex in Switzerland based on long-term experimental data,” *Energy Build.*, vol. 36, no. 6, pp. 543–555, Jun. 2004.
[194] J. F. Nicol, M. A. Humphreys, and B. Olesen, “A stochastic approach to thermal comfort - Occupant behavior and energy use in buildings,” *ASHRAE Trans.*, vol. 110, pp. 554–568, Jan. 2004.
[195] B. Jeong, J.-W. Jeong, and J. S. Park, “Occupant behavior regarding the manual control of windows in residential buildings,” *Energy Build.*, vol. 127, pp. 206–216, Sep. 2016.
[196] US EIA, “Residential Energy Consumption Survey,” 2009. [Online]. Available: https://www.eia.gov/consumption/residential/data/2009/.
[197] Natural Resources Canada, “Water Heater Guide.” Oct-2012.

ANNEX

Annex A1. Towards A Comprehensive Tool To Model Occupant Behavior For Dwellings That Combines Domestic Hot Water Use With Active Occupancy

Abstract

In building simulation, deterministic reference load profiles are normally used to represent domestic hot water (DHW) demand. Limited studies are found in the literature about the stochasticity of DHW consumption. As an attempt to fill this need, a stochastic end-user DHW demand model was constructed with temporal coherency with a well-known occupancy generator. The tool uses aggregated data from national surveys to effectively scale occupant behavior models built in different parts of the world to produce the output for a given configuration. This tuning procedure is necessary to account for variations of occupant behavior between different countries. The model displayed great accuracy in predicting the building DHW demand when its outputs were compared with measurements made in a multi-residential building in Quebec City, Canada. At its current status, the tool can be used for US, Canadian and UK dwellings, but the idea could be expanded for other locations.

A1.1. Introduction

Residential buildings are responsible for 31% of world's energy demand [191] and their consumption has been constantly increasing over the last few decades [192]. Fortunately, it is possible to greatly reduce energy use in buildings mainly by teaching individuals to adopt a low carbon lifestyle [86], [87]. The energy consumption of a building turns around occupant behavior. This has been seen in energy monitoring studies carried out on identical buildings, where the occupants' presence and their interactions with the buildings produce large disparities on the final bill [24]. Consequently, inadequate representation of occupant behavior in building energy simulation often leads to inaccurate predictions [193], and this cascades down to inaccurate prediction of energy retrofit, misleading results of new designs and many others.

To fix this issue, multiple deterministic and stochastic models were developed to predict occupants' actions on several aspects of the building: HVAC systems [194], window opening [195], artificial lighting [89], blinds and window opening [152], electrical appliances [101], [130] and hot water appliances [149]. These studies show promising results when compared with field studies. Currently most of the models developed are built upon country dependent data and thus building professionals cannot employ them all around the world without inducing errors in occupant behavior representation. As occupant behavior depends on socio-economic factors, it is expected that cultural differences lead to differences in occupancy and thus occupants in various countries might act diversely [95]. One solution to this problem is to replicate the monitoring process required for the development of these models in multiple countries so that they can be adapted for different lifestyles. This option is cumbersome as field survey monitoring asks for large time and financial resources. Re-doing the same task for multiple regions of the world is also unnecessarily repetitive.

Moreover, the tools presented above have been done independently. The modelling of the occupancy of Richardson and the window opening of Robinson, for example are in principle disconnected. The authors firmly believe that the building simulation community could benefit of a line of research with the purpose of the creation of comprehensive tools that merge all this aspects of human behavior together.

This paper attempts to find an alternative manner of accounting for the variations in occupant behavior between different countries by using a stochastic tool created with data coming from a specific country and adapting it for another country with a tuning procedure based on aggregated national statistics. In this attempt, the authors adapted to the Canadian lifestyle a domestic hot water (DHW) demand profile generator developed for the US by looking at national averages regarding the use of water in households.

DHW represents a substantial proportion of energy consumption in buildings. In the US, 18% of the energy demand in the residential sector is due to water heating [196]. Furthermore, as buildings are getting more efficient in terms of space heating and cooling, this ratio is expected to increase over the years, meaning that solutions to reduce building environmental footprint should consider the energy used for DHW.

The lack of interconnection between occupant models is also occurring on DHW models. Although some models consider its connection [117], [159], DHW demand tools usually do not look at both the number of occupants living in a household and the actual number of occupants in the household at a given time as a time series, even if the use of DHW should be proportional to these values. Instead, few models merely propose a simplified classification of the type of consumption in the dwelling (low, medium or high consumption). By combining a DHW model with a model that creates stochastic occupancy schedules in the building, more representative results are expected. This paper first describes the procedure used for both the incorporation of an active occupancy model into a DHW demand model and also the alterations made with national data to adjust these tools from a given country lifestyle (respectively the United Kingdom and the United States) to a Canadian one. To assess the accuracy of this novel methodology, in the last part of the paper, the profiles produced by the newly developed tool were compared with DHW consumption measurements made in a multi-residential building in Quebec City, Canada.

A1.2. Methodology

In order to create a DHW demand tool that accounts for occupancy schedules of the dwelling, two occupant behavior tools were merged together: one that projects occupancy [99] and one that predicts DHW consumption [100] both for residential buildings. It is important to consider occupancy in buildings when forecasting DHW use, as the number of events related to DHW use is expected to be proportional to the number of people present in the building.

The newly developed tool uses a time step of 10 minutes and only needs two inputs: first, the number of simulated dwellings and second, the number of days simulated (usually 365 days, i.e. one year). For every time step and dwelling, the outputs are the number of occupants and the volume of DHW being used in that time step.

To do so, the model starts by assigning a value for the number of people living in every dwelling using a probability distribution established from Canadian household statistics [108]. With these values, the model generates one annual occupancy profile per dwelling. Based on this schedule, the tool predicts the DHW consumption by forecasting the events (start and volume). The summation of overlapping events in each time step gives the actual volume needed. Fig. A1.1 summarizes the procedure used by the model.

As the selected tools are based upon data coming from different countries, a scaling had to be done to adapt them for differences in behavior. The following subsections explain how these models work, the methodology behind the tuning of these models and its impacts on the outputs.

A1.2.1. Active occupancy model

Active occupancy is defined here as the periods when an occupant is physically active in their house (not sleeping). During this period, the occupant is not necessarily interacting with the built environment, but has the capacity to do so. A very popular tool found in the literature for the creation of realistic stochastic daily active occupancy profiles is the one developed by Richardson et al. [99]. As it is available online, this model is easily accessible for everyone and was thus chosen as the basis for the active occupancy part of the tool described in this paper.

Richardson's tool employs a first order Markov-Chain method to generate stochastic occupancy profiles with a 10-min resolution. A first Markov-Chain refers strictly to the current state to determine change of state and does not consider any preceding states – it is a memoryless methodology. As a result, only two variables determine the probability function for the number of active occupants in a dwelling at a given time step: the hour-of-day and the number of occupants during the previous time step.

To obtain these probability transition matrices, Richardson et al. use the results of a Time Use Survey, which contains 20,000 weekly United Kingdom household journals detailing time use by 11,600 people at a 10-min resolution [107]. The number of active occupants was found at each time step and the following, enabling the calculations of transition probabilities. This is an extensive work and such detailed data is not available in all countries, hence a need for a simple way to adjust Richardson's tool for other countries.

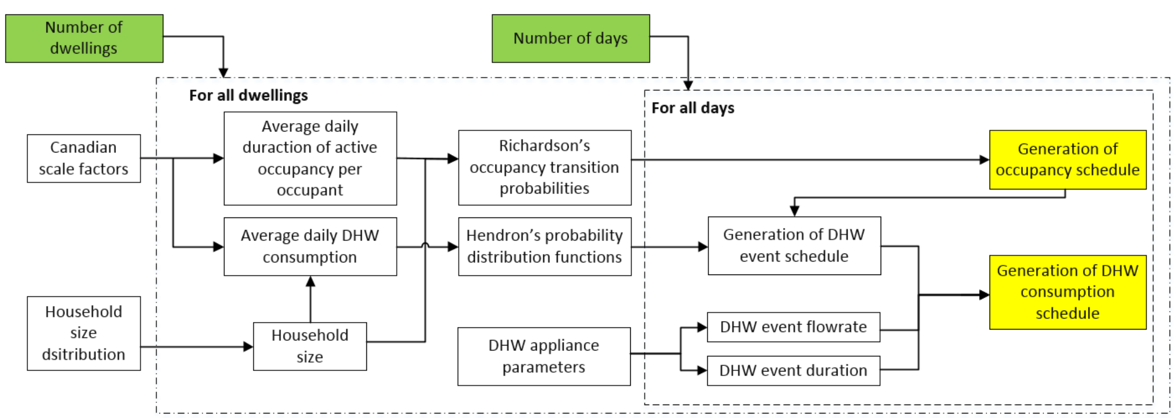


Figure A1.1. Schematic breakdown of the domestic hot water model showing the relationship between all components. Green boxes refer to inputs provided by the model user. Yellow boxes are the output of the model.

According to the UK Time-Use Survey, British citizens spend on average 1,003 minutes per day in their home and sleep for 476 minutes, meaning that they are actively living in their dwellings for 527 minutes per day. In Canada, these numbers are 990 minutes at home, 498 minutes of sleep and consequently 492 minutes of active occupancy [112]. Accordingly, for Richardson's tool to be reliable in Canada, the probability transition matrices must be adjusted so that on aggregate, the time spent by occupants in the dwelling is reduced by 6.6%. Evidently, the major assumption behind this procedure is that other than the total amount of time spent awake in their home, people in different countries follow identical occupancy patterns, which might not be true in different regions of the world, but it is an acceptable premise considering the lack of data to adopt any other.

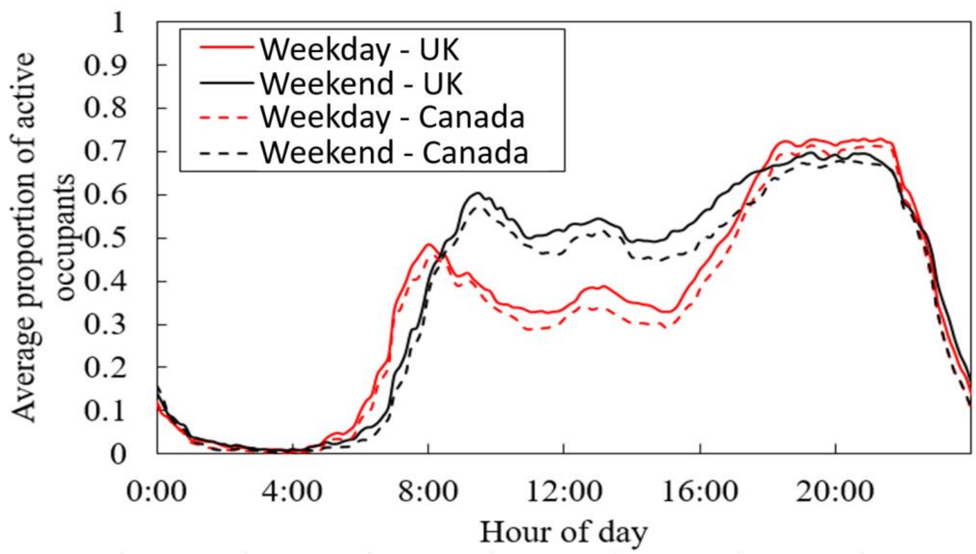


Figure A1.2. Comparison of aggregated daily active occupancy from Fichardson's tool before (solid lines) and after (dashed lines) the suggested adjustement.

The adjustment made to Richardson´s model was tested with real data. For this, it was run 1,000 times before and after the adjustment for a weekday and a weekend day. Similar tests have shown that 1,000 simulations is an adequate number of runs to obtain aggregated results as little improvement in terms of accuracy is found afterwards [113]. A comparison of the averaged model output before and after the change is presented in Fig. A1.2.

The graph shows without surprise that the patterns of occupancy after the scaling (dashed lines) are very much like the ones observed with the original model (full lines). The only difference is that the dashed lines have a proportion of active occupancy smaller than the full lines as the integral of the new curves are equal to the targeted value.

A1.2.2. Domestic hot water model

For this paper, the stochastic DHW tool developed by Hendron et al. is used to simulate consumption profiles together with occupancy profiles. Hendron´s tool is also available free of charge and includes realistic details such as vacation periods and seasonability [100]. This model divides hot water consumption in five major end-use categories: shower, bath, clothes washer, dishwasher, and sink. For these five categories, a probability of use at each hour is given based on two datasets coming from dwellings from US [121], [124].

Adjustments are then applied to the probabilities using calibration scalars to reflect differences per type of day (weekday/weekend) and season. Once a hot water event is assigned a starting time, the flow rate and duration are obtained from different probability distribution functions (pdfs), providing the amount of water used in each hot water event.

Five alterations were implemented to fit Hendron’s model with the tool developed in this paper. First, the resolution of Hendron’s start-time pdfs for the five considered water appliances were adjusted from one hour to ten minutes so that it could work with the occupancy model. This increase in resolution was done by linear interpolation.

Second, the curves were adapted so that they could reflect a Canadian lifestyle instead of an American one (from which there were first developed). Table 3.1 shows the average daily volume of consumption by the five hot water appliances considered in the tool from US [121] and Canada data [197], for a household of three people. In the US, the sum of these five appliances adds to a total of 195 litres of DHW per day. In the Canadian data, this value is 225 litres per day.

Consequently, if one uses an unaltered version of Hendron's model to simulate DHW consumption in a Canadian building, it would lead on average to underestimating the consumption by approximately 13%. The data from Table 3.1 was used to properly scale the probability distribution for each of the end-uses.

Next, a calibration scalar based on the number of occupants living in the dwelling was added (third modification). The probability of DHW use is directly proportional to the number of people and thus a five-people household is expected in the model to consume more DHW than one based on one-person. The Canadian building simulation software HOT2000 proposes to use a slope of 35 litres per person when accounting for occupancy during forecasts of daily hot water consumption [122]. Subsequently, for every simulated household, the tool checks its size and assigned an appropriate value to this calibration scalar.

To have a consistent occupant behavior model, there must not be DHW use for the shower, the bath and the sink when there is no one in the dwelling. Thus, a fourth change was implemented to ensure that the result does not lead to incoherent outputs. For each occupant, the tool attributes the pdfs and then looks at the simulated active occupancy profiles of the household to change these pdfs to guarantee that the occupant is not consuming DHW when he is not awake in the dwelling. To ensure that the aggregated amounts of daily DHW use is unaffected by this change, the area under the new curves must be equal to the area under the old ones. Therefore, the modified probability distributions are multiplied by a correction factor.

Figure A1.3 offers an example of such an adjustment for occupancy for the probability distribution of shower use in a two-occupant house. It is clearly observable that there is zero chance of a shower occurring when zero occupants are in the building. At any other time, the new probability curve follows the patterns of the old one, but with increased values which depends on the number of occupants in the dwelling. These values are calculated so the overall DHW use is not modified. This procedure is repeated for every simulated day and appliance, and each day has different probability distributions according to the active occupancy profile.

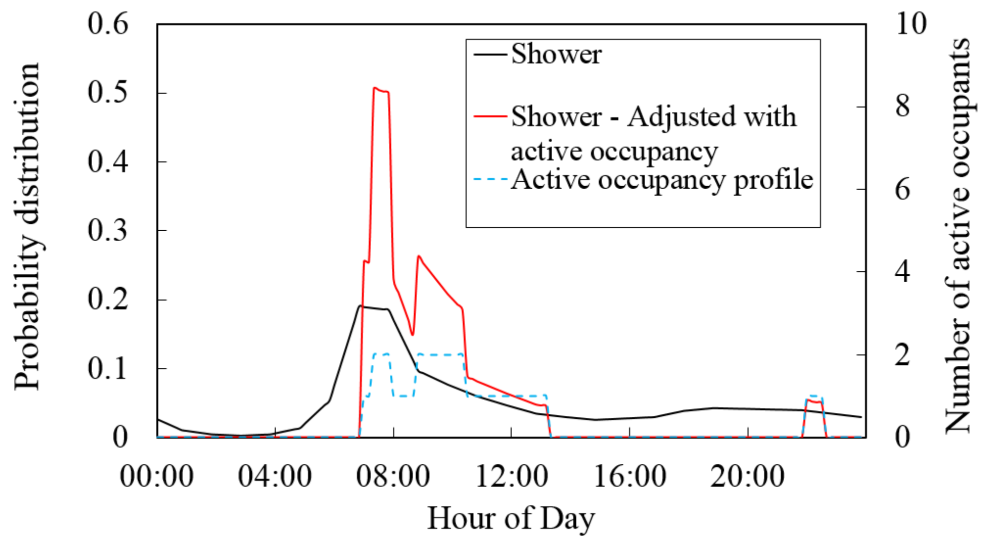


Figure A1.3. Example of probability distribution of a shower event before and after fitting the curve with active occupancy profile.

To evaluate the influence of this modification, Fig. A1.4 presents the aggregation achieved by repeating this procedure 1,000 times. The graph exposes the impact of active occupancy, which is shown in blue, on the probability of a shower event. If there was no influence, the black and red curves would perfectly be superimposed. Yet, the morning peak happens an hour later than it does in the Hendron probability curve. This could be explained by the British origins of the occupancy model versus the American character of Hendron's tool. One could theorise that Americans leave their home one hour earlier than British. In the evening, the changes made on the pdf induced an increase in the probability of a shower event, as this period of the day represents the peak of active occupancy. Finally, the fifth alteration introduced in the model takes low-flow water devices into consideration. As reducing buildings footprint is a priority in our society, low-flow water devices (showerheads, dishwashers, clothes washers and sinks) are becoming more widespread, which diminishes hot water consumption; these are therefore appliances worth studying. An analysis of retrofits suggests that low-flow sinks and showerheads reduce flow rates by a factor of 20% to 50% [123]. Unfortunately, no more accurate studies were found and an educated guess of 20% of flow rate reduction was chosen for this new calibration scalar, which can be applied or not to the flow rate probability distribution of each hot water appliances considered by the tool, except for baths.

In the end, these adjustments provided a DHW forecasting tool which is directly connected with occupancy and accounts for lifestyle change and for the use of water savings appliances.

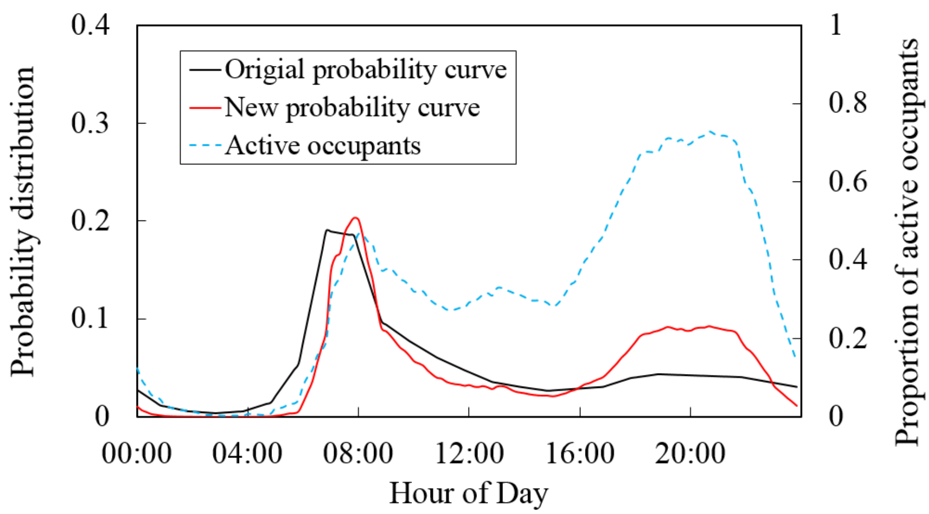


Figure A1.4. Aggregated probability distribution of a shower event before and after fitting the curve with active occupancy profile. Red and blue curves obtained after 1,000 simulations.

A1.3. Results

A1.3.1. Experimental data

To validate the procedure, the DHW output of the model was compared against measurements taken in a multi-residential building (social housing) in Quebec City, Canada. These measurements provide volume of DHW for each of the 40 dwellings of the building every 10 minutes. This dataset is independent from the tool – it was not used in the making of the model and therefore can be used for independent validation. This building was constructed with the objective of limiting energy consumption. Therefore, low-flow devices were installed in the showers and the sinks. However, tenants were not trained or educated regarding the energy performance of their apartments. Thus, measurements are expected to be representative of the everyday life of the building occupants. Unfortunately, no data provides the exact occupancy of the building, which makes it impossible to directly validate this part of the model. Nevertheless, a favourable comparison between the measured and simulated available data would provide an indirect verification of the occupancy model as it is tied to the DHW model.

The monitoring duration considered for the validation of the model is four months (January to April 2016). During this period, the building used a total 673,244 L, which translates into a daily consumption of 139.1 L per household, a number much smaller than the average Canadian value of 225 L for a family of four people. One dwelling was mostly unoccupied during the validation period, which could be seen by the fact that it had one single day of non-zero DHW consumption. Discarding this household, the sample size is 39 dwellings and the average becomes 142.7 L per day. The average standard deviation in the day-to-day consumption of a dwelling is 70.9 L.

In their monitoring study of 119 homes in Halifax, Canada, George et al. foreshadowed this difference in DHW consumption between the case study building and national aggregated data [68]. This decrease can be explained by declining household sizes, by the use of water saving devices and by changes in occupant behavior. The alterations made to the DHW tool should account for the first two explanations.

Figure A1.5a shows a side-by-side daily DHW consumption of the individual dwellings in a box-and-whisker plot. It confirms the substantial differences in use of hot water between households, increasing from an average of 17.5 L for the lowest consumer to a mean value of 495.9 L for the largest. There is also a large day-to-day variability between dwellings. Some households consume a very consistent volume of DHW day after day and others do not. For example, despite a similar median day, its narrower box illustrates that the day-to-day consumption in dwelling #22 is much more consistent than in dwelling #21. Several households appear to have developed steady DHW consumption habits and hence have a small day-to-day standard deviation. However, this does not seem to be the case for heavy consumers, as dwellings from #31 to #39 have large boxes and whiskers.

A1.3.2. Simulation results

By setting the number of dwellings and number of days to be simulated to respectively 39 and 121, the demand of DHW of the case study building is predicted by the tool. The adjustment for low water devices is turned on to adequately represent the appliances found in the building. The simulations predict an average daily consumption of 141.0 L per dwelling, with an average daily standard deviation of 61.6 L.

Figure A1.5 displays the distribution of hot water use in the building. Two notable differences are found between Fig. A1.5a, obtained from measurements, and Fig. A1.5b, generated from simulations. First, the variation in DHW demand between the dwellings is much smaller in the simulations than in reality. Simulation results range from an average daily consumption of 91.4 L to an average of 221.9 L. For the simulations, the differences in DHW consumption between the dwellings are strictly driven by differences in household sizes, hence the lower variability in consumption than the one found with measurements. No consideration was made in the model for the type of consumers that make up the simulated households. In real life, some people typically use more DHW than others and thus the model could be improved in the future by accounting for that. Without this addition, and despite the stochastic aspect of the tool, over a large number of days, households of equal size will consume a highly similar total volume of DHW. An alternative to this drawback would be to generate a single day DHW profile for every household and replicate this profile for every day. In that way, the stochastic effects would not be cancelled or averaged over a high number of days. However, this alternative offers no day-to-day deviation in the DHW consumption of a dwelling, which is also not realistic. Another solution would be to simply infer differences in types of consumer with the addition of another calibration scalar.

Second, the day-to-day variability in each dwelling is very alike in all simulated dwellings, as evidenced by the similar length of the boxes and whiskers in Fig. A1.5b. Fig. A1.5a shows a different pattern for the measured data, in which variability is highly different between dwellings, as mentioned before. Since the tool is purely probabilistic, no daily routine is considered in the simulations.

Consequently, for all dwellings, the DHW consumption profile can completely change day after day. To test the model variability in DHW use for the complete building, its total annual consumption was simulated 1,000 times. During this test, the average daily consumption of the building ranged from 125.8 L per dwelling in the building profile that generated the lowest amount of DHW to 164.1 L, with a mean value of 141.9 L and a standard deviation of 6.2 L. These variations are purely due to changes in the number of people living in the building, as proved by Fig. A1.6 which gives the relation between household sizes and volume of DHW. Each dot provides the average household size and average daily volume of DHW for each simulation.

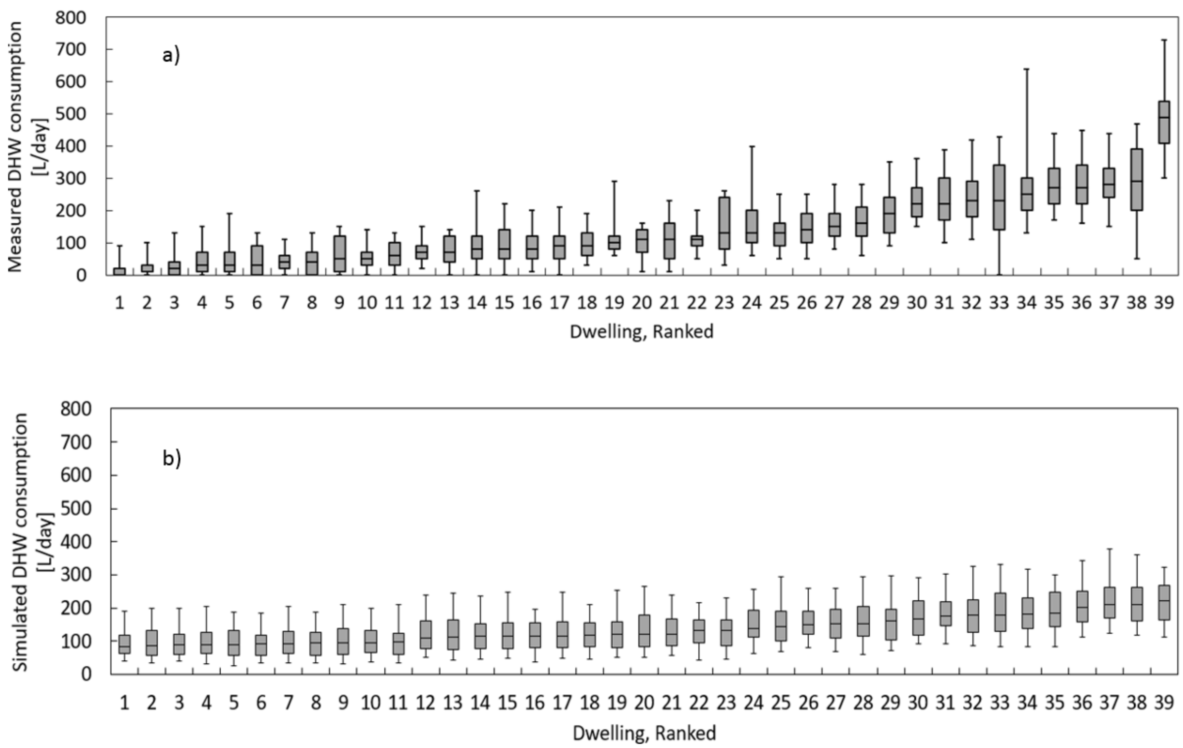


Figure A1.5. a) Measured and b) Simulated daily DHW consumption in the 39 dwellings during the validation period. Line within the box shows median day, length of the box shows the 1st and 3rd quartile and height of whiskers shows 5th and 95th percentile.

The linear regression shown in Fig. A1.6 has a coefficient of determination R^2 = 0.98. In reality, this value is expected to be lower due to divergences in types of consumers. For example, George et al. measured a coefficient of R^2=0.94 in their study when correlating consumption with household sizes [68].

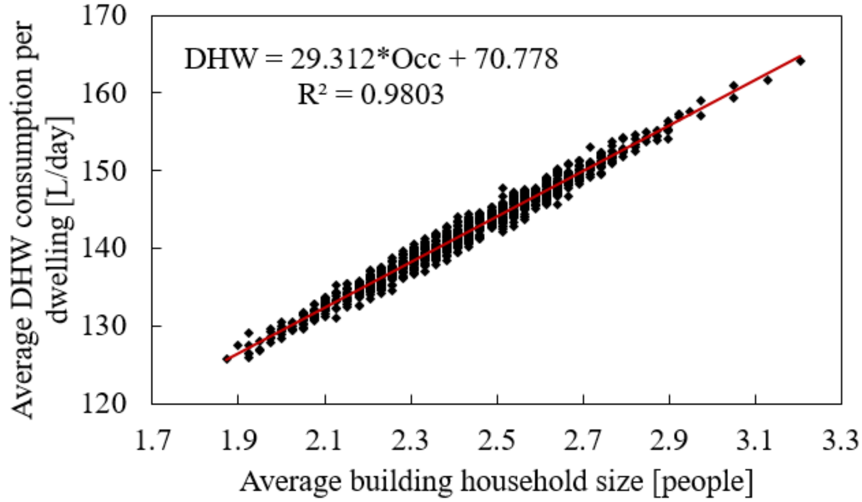


Figure A1.6. Effect of the average household size of the building on its DHW demand.

Although this represents a high coefficient, it is not as close to a perfect fit as the model predicts. Nevertheless, the slope and intercept of the regression curve is comparable with those found in different DHW monitoring studies. A slope of 29.31 L per day per occupant is smaller than the targeted value of 35 that is used by HOT2000, but that is explained by the adjustment made for low-flow devices. It is also interesting to see the variability of household sizes in the building. Fig. A1.6 reveals that if the case study building follows typical Canadian distributions, then the minimal number of people living in the building is 73 people (1.87 occupants per household) and the maximum is 125 people (3.13). These values can be used to calculate the possible range of different building parameters, such as the electricity consumption or heat gains due to the occupants. The average building population found during the 1,000 simulations is 94.6 people with a standard deviation of 8.14 (an average household size of 2.43±0.21 people).

A1.3.3. Impact of considering occupancy profiles

One of the main contributions of this paper is the merging of an occupancy profile model within a DHW consumption prediction tool by preventing the use of specific hot water appliances by an occupant when he is not predicted to be awake in the dwelling. This modification was made with the objective of developing a comprehensive occupant behavior model. However, as confirmed by Fig. A1.4, this procedure affects the daily probability distribution of the starting time use of hot water appliances and thus it could modify the daily profile of DHW consumption in the building. This subsection analyses whether this change improved or degraded the accuracy of the tool.

To do so, a new intermediary tool was developed in which occupancy schedule is not considered. In essence, this intermediary model is Hendron's tool with scale factors applied for household sizes and to adapt it to Canadian behaviors, so that the total volume of DHW should be the same between the intermediary and the complete tools.

Figure A1.7 presents the average daily DHW profiles generated by the complete and the intermediary tools and compares those profiles to the one observed in the case study building. The total DHW volumes of the simulated profiles are nearly identical to the measured volumes. The measurements show that there is a clear peak of consumption in the building during the evening. This peak is also present in the complete tool which predicts a flowrate that is nearly identical to the one measured. However, this is not true for the intermediary model as this model underestimates the evening peak by approximately 25%. A water heating system based on such a profile could potentially lead to a lack of hot water for the occupants during the evening. Nevertheless, in the early part of the day (from midnight to 7:00 AM), the adjustment for occupancy schedules has created an underestimation of DHW consumption. As foreshadowed by Fig. A1.4, in the measured dataset, the morning increase happens around 6:00 AM, while it happens at 7:00 AM in the simulations that accounted for occupancy schedules. Again, this could be explained by the fact that the occupancy schedules generated in the model are based on British patterns which might not exactly reflect Canadian lifestyle. A more accurate way to generate schedules that fit with Canadian patterns could fix this problem.

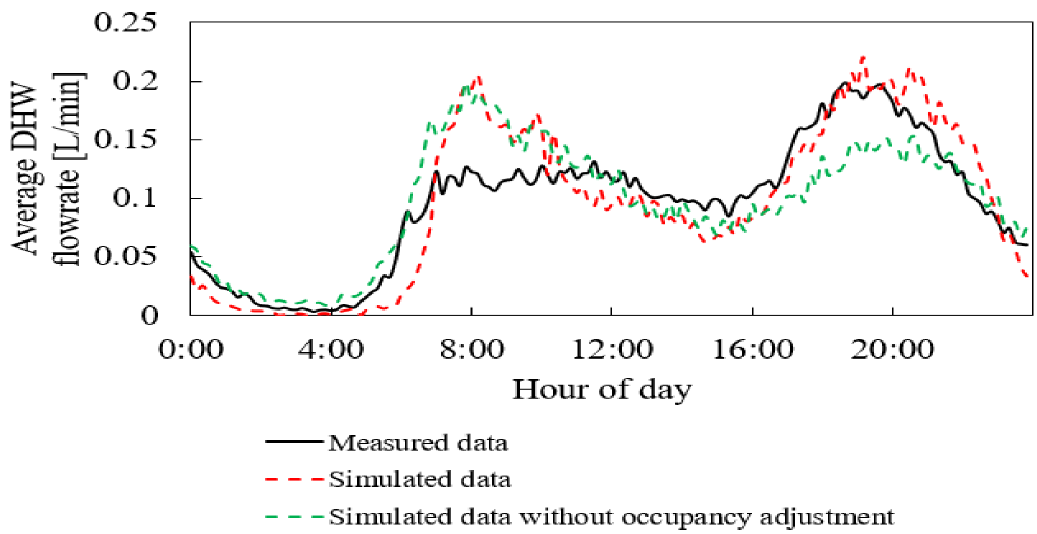


Figure A1.7. Average daily DHW profile from measurements (full line) compared to the one obtained by the model, with and without the adjustement for occupancy schedules (dashed lines).

The main difference between the measured and simulated datasets is in the morning. With or without an adjustment for occupancy schedules, simulations predict a morning peak that is not seen in reality. It seems like the occupants living in the studied building do not follow a "usual" daily DHW schedule as morning peaks are seen in most DHW monitoring studies [68], [134].

In short, the occupancy schedule adjustment improved predictions in the evening, but it also decreased accuracy during the night and beginning of the morning. Fig. A1.8 plots the simulated building DHW flowrate versus the measured one for all 144 time steps of the average day. Fig. A1.8 confirms the observations made from Fig. A1.7 since it is clear that the model accounting for occupancy is better at predicting consumption peaks (i.e. when the measured flowrate is above 0.15 L/min), but is less accurate in low-flow periods (i.e. below 0.09 L/min). Regression coefficients between the black line and the two simulated datasets are R^2 = 0.64 for the intermediary model and R^2 = 0.73 for the complete model, showing that accounting for occupancy schedules did improve the accuracy of the model. Moreover, linking DHW consumption with occupancy represents an initial step in the development of a comprehensive occupant behavior model. Other behaviors, such as electricity consumption and window opening control, can all be merged together using the same procedure.

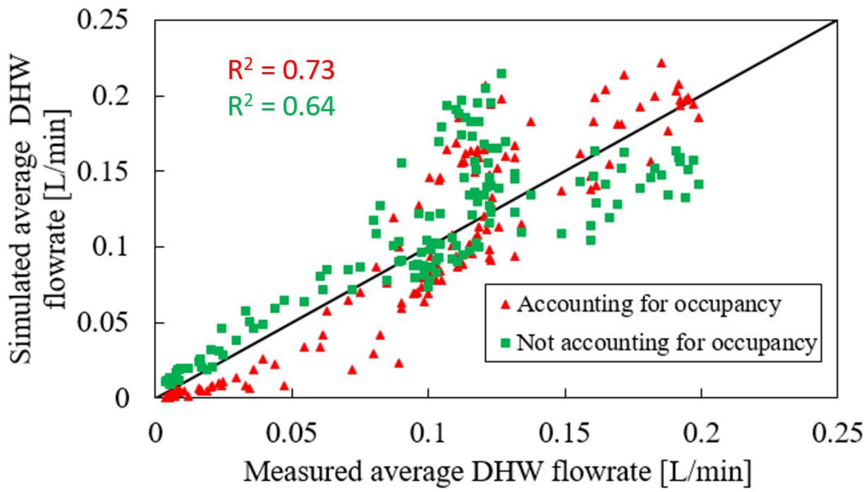


Figure A1.8. Comparison of simulated data with measurements. Red triangles represent data coming from the model with adjustment for occupancy schedules and green squares are data coming from the model without the adjustement. Simulated and measured values are in agreement when markers fall on the black line.

A1.4. Ongoing and future work

Ongoing work is refining the model with the addition of a probability distribution curve which modifies the per capita DHW consumption of households so that the model can depict different types of consumers. This parameter is expected to follow a lognormal distribution [68]. Validation of the tool against a British dataset is also currently made to test the idea with another cultural background [134]. Once this is achieved, the objective is to add electricity consumption and set point temperature using a methodology similar to the one employed for DHW. The occupancy behavior tool could then be linked to a dynamic building simulation software (such as Energy Plus or IES) to represent complete stochastic occupant behaviors that are in accordance with different country lifestyles. Work also needs to be done to make the tool entirely accessible for anyone to use.

A1.5. Conclusion

This paper presents the first step of a new consistent and comprehensive occupant behavioral tool that uses scaling factors to account for differences in behavior between countries. The part of the tool shown here is the one that generates DHW profiles for a given number of days and dwellings using a combination of previously made DHW and occupancy models. These two tools are stochastic models that are combined to ensure that no consumption happens when no one is in the building and that the total volume of DHW is coherent with the number of people living in the dwelling. Differences in lifestyle between countries are accounted for by multiplying probability matrices by calibration factors that are obtained using aggregated national statistics.

To validate the tool, its output was compared with measurements coming from a multi-residential building in Quebec City, Canada. Analysis of this dataset showed high variations of the average daily consumption between every dwelling. Furthermore, the day-to-day variability in a single household is very different from a dwelling to another, as if no family adopts the same behavior concerning DHW. This demonstrates the need of considering stochasticity when modelling occupant behavior in multi-residential buildings.

Simulations made from the developed tool did offer an accurate estimation of the building average consumption. However, it was unable to replicate the various patterns found in the measurements as it greatly underestimated the deviations between every household. The authors propose the addition of another probability distribution curve that covers all types of behavior to fix this problem.

The simulated profiles were able to adequately depict the evening peak of consumption of the real building, but it also predicted a peak in the morning that is not seen in measurements. Accounting for occupancy schedules improved the accuracy of simulation results.

Overall, results presented in this paper are encouraging for the development of the occupant behavior tool. It would be interesting to test the tool in a country that has a completely different cultural background (e.g. Japan or Brazil) to see if the tuning procedure can still offer satisfying results.