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Stochastic activity-based approach of occupant-related energy consumption in residential buildings

Toufic Zaraket

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Toufic Zaraket. Stochastic activity-based approach of occupant-related energy consumption in residential buildings. Engineering Sciences [physics]. Ecole Centrale Paris, 2014. English. NNT : 2014ECAP0033 . tel-01087894

HAL Id: tel-01087894

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**ÉCOLE CENTRALE DES ARTS
ET MANUFACTURES
« ÉCOLE CENTRALE PARIS »**

THÈSE
présentée par

Toufic ZARAKET
pour l'obtention du

GRADE DE DOCTEUR

Spécialité : Génie Industriel

Laboratoire d'accueil : Laboratoire Génie Industriel

SUJET :

**Stochastic Activity-based Approach of Occupant-related Energy
Consumption in Residential Buildings**

**Modéliser les Consommations d'Energie des Occupants de Bâtiments
Résidentiels par une Approche Stochastique Basée sur l'Activité**

soutenue le : 31 mars 2014

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2014ECAP0033

Abstract

The building sector is considered as a major energy consumer and pollution source among all economic sectors. It accounts for important shares, ranging between 16 and 50 percent, of national energy consumption worldwide. Reducing these consumptions and emissions is thus an important step towards sustainable development. Recently, the shift towards constructing low-consuming and nearly zero-energy buildings lead to further requirements with regard to performance and sustainability, and thus caused the design process of buildings to be more complex. Occupants' behavior is now considered as a key determinant of building's energy performance especially in the case of green buildings. Yet, energy simulation tools used in buildings industry nowadays are not capable of providing accurate estimations of occupant-related energy demands. Therefore, buildings and energy experts are devoting considerable efforts on developing more precise methods for modeling and forecasting occupants influence on whole building performance. Such models can provide accurate energy estimates and can assess future consumption variability. Consequently, building experts may improve their technical solutions, ameliorate their service performances, and promote targeted incentives.

The objective of this dissertation is to propose a model for forecasting occupant-related energy consumption in residential buildings, while accounting for variability in consumption patterns due to diversity in occupants' socio-demographic and economic profiles. A stochastic activity-based approach is thus adopted. By activity-based, it means that energy consumption of a household is estimated by summing up the energy use of different activities performed (such as cooking, washing clothes, etc.). The stochastic nature of the model is due to the probabilistic mapping established between household attributes from one side (household type, number of occupants, etc.) and the corresponding appliance ownership, appliance characteristics and power rating, and activity quantities from the other side. In order to establish these stochastic relations, a fairly sufficient number of households' characterizing attributes is taken into account. The proposed model is applied for two domestic activities, namely watching TV and washing laundry. Three types of Monte Carlo simulations are performed to provide energy estimates for these two activities: for a given specified household, for randomly generated households with constraints, and for totally random population-wise households. A comparison between model's simulation results and real measured energy consumption data enables validating the model for the two considered activities. A generalization framework of the modeling approach for other domestic activities is sketched, and its possible integration into buildings design process is discussed and illustrated through a number of examples.

Keywords: *Energy consumption, residential building, energy model, green building, energy performance, building occupants, household profile, domestic activity, domestic appliance, occupant behavior, consumption variability, energy simulation.*

Résumé

Le secteur du bâtiment est considéré comme un gros consommateur d'énergie et une source de pollution majeure parmi tous les secteurs économiques. Il représente entre 16 et 50 pour cent des consommations nationales d'énergie. La réduction de ces consommations et des émissions est donc une étape importante vers un développement durable. Récemment, la transition vers la construction des bâtiments à faible consommation d'énergie a conduit à de nouvelles exigences en matière de performance et de durabilité, et ainsi encore complexifié le processus de conception des bâtiments. Le comportement des occupants est maintenant considéré comme un facteur déterminant de la performance énergétique d'un bâtiment, particulièrement dans le cas des bâtiments basse consommation (BBC). Pourtant, les outils de simulation utilisés dans l'industrie des bâtiments ne sont pas aujourd'hui en mesure de fournir des estimations fiables de la demande d'énergie des occupants. Par conséquent, les experts en énergie et bâtiments portent une grande attention à développer des méthodes plus précises pour la modélisation et la prévision de l'influence des occupants sur la performance du bâtiment. Ces modèles doivent pouvoir fournir des estimations plus précises des consommations d'énergie et évaluer la variabilité de ces consommations. En conséquence, l'objectif visé est de permettre aux experts en construction d'améliorer leurs solutions techniques, améliorer la performance de leurs services, et promouvoir des incitations mieux ciblées vers les usagers afin de réduire leurs consommations énergétiques.

L'objectif de cette thèse est de proposer un modèle pour estimer la consommation d'énergie liée aux comportements des occupants de bâtiments résidentiels, en prenant en compte la variabilité des modes de consommation au travers de la diversité des profils socio-démographiques et économiques des occupants. Une approche stochastique basée sur la notion d'activité est donc adoptée. Avec ce modèle, la consommation d'énergie d'un ménage est estimée en additionnant la consommation d'énergie des différentes activités domestiques (comme faire la cuisine, le lavage du linge, etc.). La nature stochastique du modèle est due aux relations probabilistes établies entre les attributs des ménages d'une part (type de ménage, nombre d'occupants, etc.) et la possession des équipements domestiques, les caractéristiques des appareils, leur puissance, et les quantités d'activité d'autre part. Afin d'établir ces relations stochastiques, un nombre suffisant d'attributs est pris en compte pour caractériser un ménage. Le modèle proposé a été appliqué pour deux activités domestiques, à savoir regarder la télévision et laver le linge. Des simulations de Monte Carlo sont effectuées pour fournir des estimations de consommation d'énergie pour ces deux activités dans trois cas de figure : pour un ménage spécifique, pour des ménages générés aléatoirement avec des contraintes sur leurs attributs, et pour des ménages totalement aléatoires représentatifs de la population française. Une comparaison entre les résultats de la simulation de modèle d'une part et des données de consommation d'énergie réelle d'autre part, a permis de valider le modèle pour les deux activités considérées. Un cadre de généralisation du modèle pour d'autres activités domestiques a été introduit, et sa possible intégration dans le processus de conception des bâtiments a été discutée et illustrée au travers d'un certain nombre d'exemples.

Mots-clés: *Consommation d'énergie, bâtiment résidentiel, modélisation et simulation de l'énergie, bâtiment basse consommation, performance énergétique, occupants, profil des ménages, activité domestique, équipements domestiques, comportement des occupants, variabilité de consommation.*

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List of Abbreviations

ADEME	Agence De l'Environnement et de la Maîtrise de l'Energie (French Environment and Energy Management Agency)
BBC	Bâtiment Basse Consommation (Energy-efficient building)
CREDOC	Centre de Recherche pour l'Etude et l'Observation des Conditions de vie (French research centre for the study and monitoring of living standards)
CSTB	Centre scientifique et technique du bâtiment (French scientific and technical centre for building)
EE	Energy efficiency
HEA	High environmental awareness
HH	Household
INSEE	Institut national de la statistique et des études économiques (French national institute of statistics and economic studies)
LCA	Life Cycle Assessment
RP	Reference Person
RT	Réglementation Thermique (Thermal regulation)
SABEC	Stochastic activity based energy consumption model

Nomenclature of model variables

AE_{CON_TV}	Energy consumption of the activity ‘watching TV’ per household (ON mode)
AE_{STBY_TV}	Energy consumption of the activity ‘watching TV’ per household (Standby mode)
AE_{TV}	Energy consumption of the activity ‘watching TV’
AG_{RP}	Age of household’s reference person
AP_{Tech}	Appliance technology
AS_{RP}	Activity/Employment status of the reference person
ASU_{HH}	Aggregated service unit of an activity
ASU_i	Individual service unit of an activity
\overline{BSA}	Mean body surface area of an adult
CR_i	Changing rate of clothes per individual
C_{WM}	Capacity of a washing machine
DC_{hh}^m	Quantity of dark-colored clothes washed per household month
EAL_{HH}	Environmental awareness level of a household
EC_{wm}	Energy consumption of the activity “washing laundry per household per month
EL_{RP}	Education level of household’s reference person
EL_{WM}	Energy label of a washing machine
\bar{H}	Mean height of an adult
HH_{Type}	Household Type
H_i	Height of an individual
I_{HH}	Total monthly income of a household
I_i	Monthly income of an individual
LC_{hh}^m	Quantity of light-colored clothes washed per household per month
P_{ON}	Power rating of an appliance for the ON mode
P_{STBY}	Power rating of an appliance for the standby mode
$P_{WM,T}$	Power rating of a washing machine at temperature T
\overline{QC}	Mean weight of clothes dressed by an adult per day
QC_{HH}^m	Total quantity of clothes laundry per household per month
QC_i^d	Quantity of clothes dressed by an individual per day
QC_i^m	Quantity of clothes dressed by an individual per month
SPC_{RP}	Socio-professional class of household’s reference person
\bar{W}	Mean body weight of an adult
WC_{wm}	Water consumption of the activity “washing laundry per household per month

W_i	Body weight of an individual
BSA	Body surface area of an individual
F	Parameter representing the energy efficiency of the appliance
FR	Filling ratio of washing machine's drum
FR	Number of washing cycles per household per month (washing laundry activity)
G	Gender
I	Income
NO	Number of occupants per household
$P(AP)$	Probability of ownership of an appliance
$P(EAP)$	Probability of owning an energy-efficient appliance
$P(AP/HH_{type})$	Probability of owning an appliance given the household type
$P(AP/AG)$	Probability of owning an appliance given the age
$P(AP/SPC)$	Probability of owning an appliance given the socio-professional class
$P(EAP/AG_{RP})$	Probability of owning an energy-efficient appliance given the age of reference person
$P(EAP/EAL_{HH})$	Probability of owning an energy-efficient appliance given the environmental awareness level of the income
$P(EAP/I_{HH})$	Probability of owning an energy-efficient appliance given the household income
$P(HEA/AG_{RP})$	Probability that a household has a high environmental awareness given the age of the reference person
$P(HEA/EL_{RP})$	Probability that a household has a high environmental awareness given the education level of the reference person
$P(HEA/I_{HH})$	Probability that a household have a high environmental awareness given the income of the household
$P(HEA_{HH})$	Probability that a household has a high environmental awareness
S	Sharing coefficient of an activity
W	Parameter representing the possession of an appliance
q	Ratio of light-colored clothes over the total quantity of clothes per household

Statistical Parameters

m	Minimum value
M	Maximum value
μ	Mean value
σ	Standard deviation
χ	Median value

Foreward

The present PhD was conducted in collaboration between BOUYGUES Construction and the Industrial Engineering Laboratory (LGI) of Ecole Centrale Paris under a CIFRE contract (Conventions Industrielles de Formation par la REcherche) between March 2011 and February 2014.

The work of this PhD is a part of a larger research and teaching chair initiated by Bouygues Construction in October 2010. This chair, called "Sustainable Building and Innovation" (Bâtire Durable et Innover), was established and funded by Bouygues Construction in partnership with three French engineering schools and their respective foundations (Ecole des Ponts Paris Tech, Ecole Centrale Paris and Supelec) and the French Scientific and Technical Centre for Building (CSTB). The aim of the chair is to support research into low-carbon technologies, sustainable buildings and sustainable neighborhoods and towns.



Acknowledgements

It would not have been possible to write this doctoral thesis without the help and support of a number of persons around me, to only some of whom it is possible to give particular mention here.

I would like first to express my very great appreciation to my principal supervisor Bernard Yannou for his help, guidance and patience throughout the three years of my PhD. Thank you Bernard for your professionalism and for the efficacy of your supervision.

I would like to offer my special thanks to my academic supervisors Yann Leroy, Stephanie Minel and Emilie Chapotot for their contribution to my work, as well as their valuable advices and help.

I am also grateful for my supervisors at Bouygues Construction, who were always here for providing me with their professional advices and for guiding my research work. Thank you Jean Lacroix, Michel Bardou, Xavier Gauvin, Alain Vassal, Arnaud Mussat, and Rebecca Cousins. Special thanks also to Noëlie Lopes for her collaboration. I wish to acknowledge the help and guidance provided by Jean-Robert Millet from CSTB.

I would like to offer my special thanks to Jean-Francois Boujut and Anne-Marie Jolly-Desodt for accepting to review this dissertation. I would like to thank also the other members of the jury: Carolyn Seepersad and Claudia Eckert for their interest in my research work. Thank you all for your constructive comments, questions, and remarks.

I would like to thank all my colleagues at LGI. Thank you for your support and friendship. It has been really a great pleasure for me to share these three years with you. Special thanks to the beautiful and very kind secretaries Corrine, Delphine, and Sylvie.

I would like to thank all my colleagues at Bouygues Construction, especially Sylvie Antoine-Coursel for her kind support.

Above all, I would like to express my deepest gratitude and love for my father Yehya and my mother Sobheye, my brothers and sisters, and all my friends who gave me always and still their unequivocal love and support.

To the dearest person for me, my daughter Lola who is 5 years old now, I would like to express my greatest love. You were, still and will always be the light of my life and the source of my hope and greatest happiness.

Résumé étendu (extended summary in French)

Le secteur du bâtiment est considéré comme un gros consommateur d'énergie et une source de pollution majeure entre tous les secteurs économiques. Il représente entre 16% et 50% des consommations nationales d'énergie dans le monde (Saidur et al. 2007; Masoso & Grobler 2010). En France, le parc immobilier est responsable de 43 % de la consommation nationale totale d'énergie et engendre environ 25 % des émissions totales de CO₂ (ADEME 2012). Selon l'ADEME (Agence de l'Environnement et de la Maîtrise de l'Energie), le secteur du bâtiment en France est véritablement le seul, des secteurs industriels, à être en mesure de faire un progrès important pour le respect des engagements nationaux en vue de réduire les émissions de gaz à effet de serre. Par conséquent, réduire et maîtriser la consommation d'énergie et les impacts environnementaux des bâtiments représente un défi de taille pour les gouvernements et les acteurs de la construction.

A l'instar d'autres pays développés, la France a mis en place récemment un certain nombre de normes et de réglementations afin de promouvoir le Développement Durable dans le secteur du bâtiment. La dernière réglementation thermique française qui définit les normes de performance des bâtiments est la RT 2012, pour « Réglementation Thermique 2012 ». Cette réglementation vise à diviser par trois la consommation d'énergie des bâtiments neufs. En conséquence, les acteurs de la construction en France privilégient de plus en plus la construction de bâtiments écologiques à haut rendement énergétique dits BBC (Bâtiment Basse Consommation). En outre, un engagement de performance entre les constructeurs et les propriétaires de bâtiments, appelé « Contrat de Performance Energétique » ou CPE, représente une nouvelle attente du marché émergent en France (CPE 2012). Par ce contrat, les constructeurs s'engagent à livrer un bâtiment énergétiquement efficace et à garantir cette efficacité (mesurée en MWh et transformée en Euros) sur un nombre d'année à venir. Récemment, la transition vers la construction des bâtiments à faible consommation d'énergie, voire à énergie positive (BEPOS), a conduit à de nouvelles exigences en matière de performance et de durabilité. Pour ces raisons, une meilleure compréhension des facteurs déterminants de la performance des bâtiments ainsi que leur intégration en conception, en particulier à des stades très précoces, est devenue essentielle.

La performance énergétique d'un bâtiment est régie par divers facteurs, tels que ses caractéristiques physiques (par exemple l'orientation et la surface), ses systèmes de services internes (systèmes de chauffage et de ventilation par exemple) et équipements (éclairage), son environnement externe (par exemple, température et humidité) et surtout ses occupants (Fabi et al. 2012; Yu et al. 2011). L'expérience souligne l'influence importante du comportement des occupants sur la performance énergétique des bâtiments (Swan & Ugursal 2009; Clewenger & Haymaker 2006). La consommation d'énergie dans le bâtiment dépend fortement du comportement général des occupants. Selon Ellegård et Palm (2011), la consommation d'énergie est intégrée dans la plupart des aspects de la vie quotidienne des ménages. Les individus utilisent l'énergie pour satisfaire certaines activités de la vie quotidienne telles que la conservation et la préparation des aliments, la fourniture de chaleur et de lumière et le maintien de la santé et de l'assainissement (Pennavaire 2010; Kashif et al. 2011). Des auteurs tels que Page et al. (2008), Yu et al. (2011) et Robinson (2006) expliquent que l'influence des occupants sur la performance énergétique des bâtiments peut être traduite par leur présence (les gains de chaleur internes, les émissions de polluants tels que le CO₂, la vapeur d'eau, les odeurs etc.) et les actions qu'ils effectuent (activités telles que la cuisine, la lessive etc.), ainsi que leurs interactions avec les commandes de systèmes inhérents pour ajuster l'environnement intérieur (réglage de température pour le confort thermique, réglage de l'intensité de l'éclairage pour le confort visuel etc.) . Selon Robinson (2006), les processus les plus complexes qui se déroulent dans les bâtiments sont ceux qui résultent des comportements humains. Ces interactions ont des implications importantes sur le bilan énergétique d'un bâtiment, affectant à la fois le microclimat à l'intérieur et les besoins en énergie appliquée. Robinson (2006) conclut que la présence des occupants dans un bâtiment et les activités qu'ils entreprennent sont de nature stochastique et difficile à prédire.

La consommation d'énergie peut varier considérablement entre différents ménages. Selon Swan et Ugursal (2009), le comportement des occupants dans le secteur résidentiel peut engendrer une variabilité sur la consommation d'énergie de près de 100% pour un logement donné. Des conclusions similaires ont également été démontrées dans les travaux de Clewenger et Haymaker (2006), Seryak et Kissock (2003), Emery et Kippenhan (2006), Masoso et Grobler (2010), Yun et Steemers (2011) et Pachauri (2004). Cette variation est due aux profils des occupants (attributs sociodémographiques et économiques) qui influent sur la possession des équipements et les comportements de consommation. De nombreux travaux ont identifié les paramètres

déterminants liés aux occupants tels que le nombre d'occupants, le revenu de ménage, l'âge du chef de famille (celui ou celle l'actif le plus âgé) le groupe social et le niveau d'éducation (McLoughlin et al. 2012; Guerin et al. 2000; Yun & Steemers 2011).

Au cours de la phase de conception, les experts s'appuient sur des outils de simulation pour évaluer et prévoir la future performance énergétique des bâtiments. Plusieurs outils de simulation énergétique tels que EnergyPlus, eQUEST, ESP-r et TRNSYS sont aujourd'hui disponibles sur le marché. Ces outils de simulation énergétique peuvent simuler la performance énergétique d'un bâtiment donné et le confort thermique de ses occupants. De manière générale, ils aident à la compréhension du fonctionnement d'un bâtiment selon certains critères et permettent la comparaison de différentes alternatives de conception. En général, les outils de simulation considèrent un certain nombre de paramètres comme entrées, telles que la géométrie de la construction et les conditions météorologiques. Chaque moteur de simulation énergétique est basé sur des équations et des principes thermodynamiques. Selon Fischer et Kunz (2004), les données d'entrée, en particulier les données météorologiques et les charges internes, sont généralement fondées sur des hypothèses. Par conséquent, la prédiction des valeurs absolues de consommation d'énergie via des simulations est rarement exacte (Malavazos et al. 2011). En raison de la complexité à collecter les préférences des occupants et leurs habitudes de consommation d'énergie, les outils de simulation ont donc tendance à gommer autant que possible l'influence des utilisateurs afin d'optimiser la performance du bâtiment (Page et al. 2008; Chiou 2009a). Ces outils considèrent alors les occupants comme des éléments monolithiques avec des profils standards auxquels on attribue des consommations moyennes d'énergie. En conséquence, les prévisions de performance énergétique générées par ces outils peuvent s'écarter considérablement de la réalité d'une famille donnée (Kashif et al. 2012; Malavazos et al. 2011).

Pour ces raisons, les experts en énergie et bâtiments tentent de trouver des outils et des techniques leur permettant de mieux comprendre les phénomènes complexes de consommation d'énergie dans les bâtiments. Ces travaux se consacrent notamment sur le développement de méthodes plus précises pour modéliser l'influence des occupants sur la performance énergétique des bâtiments. Un certain nombre de chercheurs soulignent que les approches stochastiques basées sur des données statistiques constituent une bonne méthode pour simuler les comportements de consommation des occupants avec plus de précision (Fischer & Kunz 2004; Subbiah 2013).

Dans la littérature, un certain nombre de techniques et d'approches ont déjà été développées pour modéliser la consommation d'énergie dans les bâtiments résidentiels. Selon Swan et Ugursal (2009), les deux grandes approches identifiées sont les approches Top-down et Bottom-up, chacune d'entre elles sont associées à des techniques scientifiques particulières. Les approches descendantes (top-down) utilisent des métadonnées telles que les statistiques nationales de consommation d'énergie pour obtenir des relations de cause à effet entre des déterminants et la consommation d'électricité. Les modèles ascendants (Bottom-up), quant à eux, utilisent des données recueillies au niveau de l'habitation individuelle pour déterminer les relations entre les caractéristiques des ménages et la consommation d'électricité. Les techniques les plus fréquemment utilisées pour les approches bottom-up sont la régression statistique et les techniques d'ingénierie (McLoughlin et al. 2012; Swan & Ugursal 2009). Le déploiement de modèles statistiques ou de régression est possible lorsque de grands ensembles de données mesurées sont disponibles. Ces modèles fournissent une bonne compréhension des modes de consommation de l'électricité car ils sont basés sur des données réelles. Leurs principaux inconvénients sont leur coût de mise en œuvre et parfois l'apparition de multi-colinéarité entre les variables. Les modèles d'ingénierie sont des approches « bottom-up » qui nécessitent des informations concernant les puissances des appareils et les caractéristiques d'utilisation finale pour construire une description des modes de consommation d'électricité. La grande force de ces modèles réside dans le fait qu'ils représentent la seule méthode capable de modéliser la consommation d'électricité sans aucune information historique sur l'utilisation de l'électricité. La difficulté associée à ces modèles d'ingénierie est la complexité de leur mise en œuvre et de leur validation.

Dans la littérature, diverses approches ont été développées pour modéliser la consommation d'énergie des occupants dans des bâtiments résidentiels. De manière générale, ces modèles peuvent être divisés en deux groupes de méthodes. Le premier groupe consiste à utiliser des données réelles obtenues grâce aux mesures in-situ afin d'extraire des courbes de charge (ou profils de charge) représentant les profils de consommation d'énergie des occupants. En utilisant ces profils de charge, des estimations de la consommation énergétique des bâtiments peuvent être ainsi déduites. Le second groupe se concentre sur le développement d'approches qui peuvent mieux représenter le comportement des occupants. Ces modèles visent à simuler les profils d'occupation (savoir quand les occupants sont présents dans le logement) et la consommation

d'énergie des occupants en utilisant des approches stochastiques. Des auteurs tels que Seryak et Kissock (2003) et Yohanis et al. (2008) ont adopté des méthodes du premier groupe. Bien que ces modèles puissent générer des profils de charge représentatifs de la consommation d'énergie des occupants, ils ne permettent pas de représenter les comportements de consommation d'énergie des occupants. D'autre part, le second groupe de méthodes utilise une autre source d'information, à savoir les enquêtes sur l'emploi du temps (Time Use Survey ou TUS en anglais) réalisées à grande échelle au niveau national. Chaque registre d'une enquête d'emploi du temps contient des informations sur les activités quotidiennes d'un individu sur les 24 heures d'une journée (Chiou 2009b). Certains auteurs ont utilisé ces enquêtes afin de représenter et modéliser la consommation d'énergie quotidienne des occupants (Shimoda et al. 2004; Yamaguchi et al. 2003; Richardson et al. 2008; Richardson et al. 2010; Widén & Wäckelgård 2010; Subbiah 2013). Parmi toutes les activités de la vie quotidienne enregistrées dans les TUS, les auteurs s'intéressent seulement à celles qui consomment de l'énergie dans les résidences. Ensuite, en appliquant des techniques stochastiques tels que Monte Carlo par chaînes de Markov (MCMC), les chercheurs peuvent identifier des patterns d'activité quotidienne impliquant une consommation d'énergie. Par exemple, Widén and Wäckelgård (2010) développent un modèle stochastique à haute résolution de la demande d'électricité en Suède en se basant sur des modèles d'activités domestiques. Ils identifient neuf activités consommatrices d'électricité, telles que le sommeil, la cuisine, la vaisselle, le lavage de tissu, la télévision, etc. Les auteurs associent alors chacune de ces activités à un ou des appareils domestiques correspondants. En définissant une courbe de charge pour chaque appareil, Widén et Wäckelgård arrivent à estimer la demande totale d'électricité par ménage. Ces dernières années, des approches issues du domaine de l'intelligence artificielle ont commencé à être appliquées pour la modélisation des consommations d'énergie dans les bâtiments. Kashif et al. (2012) proposent un cadre conceptuel pour simuler le comportement dynamique des occupants en utilisant une approche basée sur l'agent (Agent-based models). Le modèle proposé est utilisé pour simuler les consommations d'énergie de maisons intelligentes en prenant en compte les comportements dynamiques et sociaux des habitants. Quijano et al. (2010) ont également utilisé une approche basée sur les agents. Les auteurs proposent une plate-forme de simulation appelée SMACH (Simulation Multi-Agent du Comportement Humain) pour évaluer l'impact du comportement adaptatif de divers appareils électriques sur la consommation globale de logements.

L'objectif de la présente thèse est de développer un modèle paramétrique pour la prévision de la consommation d'énergie des occupants dans les bâtiments résidentiels. Les principaux objectifs visés par le modèle sont : (1) Fournir des prévisions réalistes et précises de la consommation d'énergie à une granularité très fine (2) Fournir des estimations d'énergie ventilées au niveau des ménages et des individus en fonction de leurs attributs socio-démographiques et économiques, (3) Etre en mesure d'évaluer la variabilité de la consommation d'énergie entre les différents individus et les ménages avec des attributs différents (différents profils d'occupants).

Étant donné ces perspectives de recherche, nous identifions les limites suivantes associées aux modèles issus de la littérature. Dans un premier temps, même si la plupart des modèles souligne un nombre relativement grand de déterminants de consommation d'énergie rattachés aux occupants (tels que le revenu, l'âge, etc.), ces modèles demeurent encore simplistes dans leur représentation. La variable principalement considérée pour représenter les attributs du ménage est le nombre d'occupants. Cela signifie que de tels modèles ne peuvent pas évaluer la variabilité de consommation d'énergie par exemple entre deux maisons ayant le même nombre d'occupants, mais différents attributs socio-économiques. Dans un deuxième temps, peu de travaux ont été identifiés quant à la génération de profils de consommation énergétique avec une granularité très fine. Les modèles dans la littérature ne sont pas capables de quantifier la consommation d'énergie au niveau d'une maison spécifique ou d'un individu spécifique selon leurs caractéristiques sociales, démographiques et économiques. Enfin, la plupart des modèles publiés est basée sur des données de consommations mesurées ou sur des enquêtes d'emploi de temps. L'intégrité de ces sources de données peut être critiquée car celles-ci ne représentent seulement qu'une partie de la population. Par exemple, les enquêtes d'emploi de temps considèrent seulement les activités des individus qui ont répondu à l'enquête; ainsi, tous les membres du ménage sont considérés comme ayant le même programme d'activités, ce qui n'est donc pas rationnel et peut mener à des prédictions de demande énergétique irréalistes.

L'analyse de deux contextes industriel et académique et la revue de la littérature au début de la thèse (voir chapitre 2 pour l'état de l'art détaillé) nous ont permis de formuler trois grandes questions de recherche qui sont exposées ci-après :

Question 1 : Est-il possible de décrire, caractériser et modéliser la consommation d'énergie dans les bâtiments résidentiels à travers une approche basée sur les activités ?

Question 2 : Comment modéliser et simuler la consommation d'énergie dans les bâtiments résidentiels tout en tenant compte de la variabilité des profils des ménages ainsi que de la nature stochastique des activités domestiques et de la possession d'équipements ?

Question 3 : Est-il possible d'intégrer « les modèles de consommation d'énergie par profils des ménages » dans le processus de conception des bâtiments et comment ces modèles peuvent être utilisés dans la perspective de l'amélioration de la robustesse de la performance énergétique du bâtiment ?

Pour répondre à ces questions, nous développons un modèle pour estimer la consommation d'énergie des occupants de bâtiments résidentiels, en prenant en compte la variabilité des modes de consommation à travers la diversité des profils sociodémographiques et économiques. Dans ce qui suit, nous allons exposer l'approche de modélisation adoptée ainsi que le modèle développé et ses différentes caractéristiques.

Dans un premier temps, nous proposons une vue systémique de la consommation d'énergie résidentielle où trois systèmes principaux régissent cette consommation : le système « ménage » (household system), le système « artefact » (artifact system) et le système « environnement » (environment system) (Figure 1). Le système « artefact » représente l'ensemble des objets (les objets fabriqués par l'homme) présents dans le système. Il s'agit principalement de l'habitation elle-même et des équipements présents à l'intérieur. Un logement est le lieu où les individus vivent et exercent leurs activités de la vie quotidienne. Il offre des fonctionnalités différentes pour ses occupants et est caractérisé par ses attributs physiques (superficie, âge, orientation etc.) et les équipements techniques (chauffage, refroidissement, éclairage, ventilation et auxiliaires). Les équipements personnels sont les dispositifs ou appareils électrodomestiques appartenant aux occupants et non inhérents à la construction. Des exemples de ces équipements sont le lave-linge, le lave-vaisselle et les réfrigérateurs. Ces équipements sont utilisés par les ménages pour réaliser des activités quotidiennes et ils consomment de l'énergie et de l'eau. Leurs taux de possession et leurs caractéristiques (puissance et taille par exemple) peuvent varier en fonction des attributs du ménage.

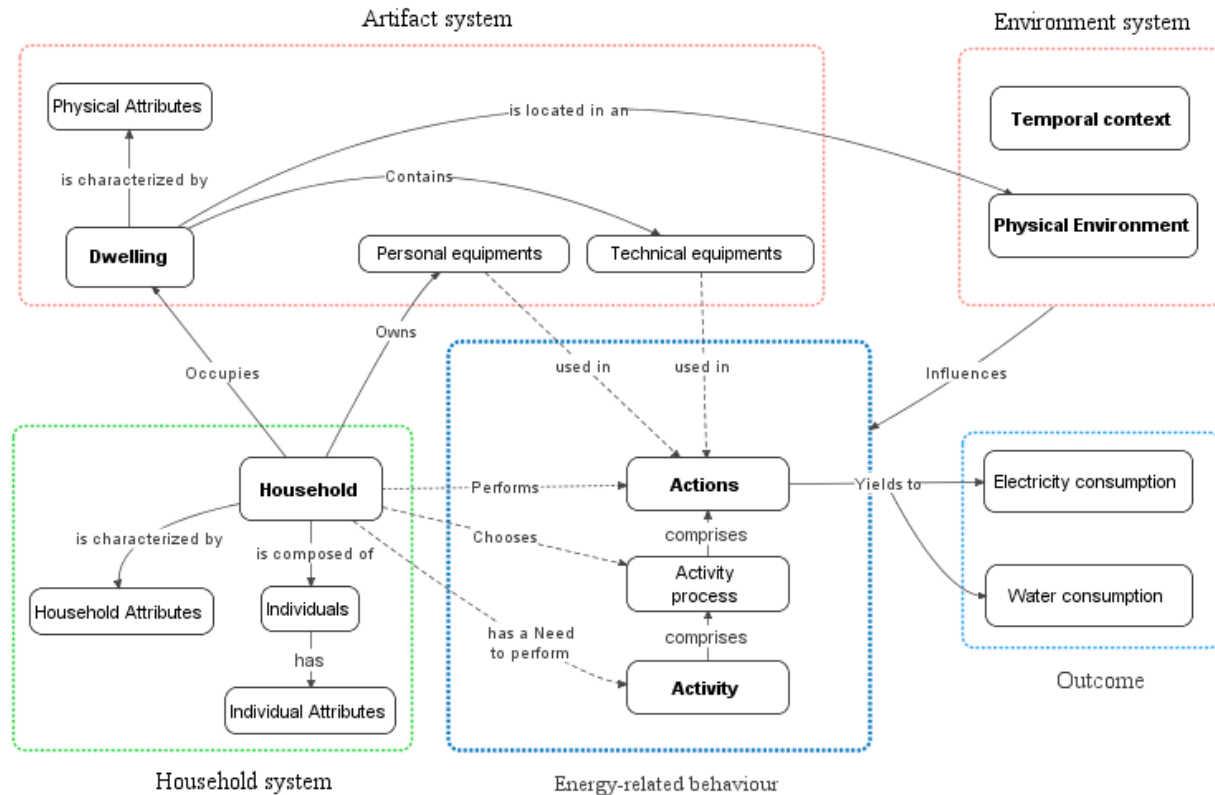


Figure 1 : Vue systémique de la consommation d'énergie dans un bâtiment résidentiel

Le système « environnement » représente les éléments extérieurs au logement, mais peuvent avoir une influence directe sur la consommation d'énergie par les occupants. Il s'agit notamment de paramètres physiques (par exemple la température et la luminosité) et de paramètres de contexte temporel (par exemple de la saison).

Le système « ménage » est constitué d'une ou plusieurs personnes vivant dans un logement. Les individus d'un ménage interagissent les uns avec les autres et avec les systèmes d'artefacts et l'environnement. Les ménages et les individus sont caractérisés par un certain nombre de variables représentant leurs attributs démographiques, socio-économiques et comportementaux. Les occupants exercent des activités domestiques pour satisfaire leurs besoins et le bien-être, tels que les activités de ménage (par exemple : vaisselle et linge), les activités de soins personnels (par exemple lavage) et des activités de divertissement (par exemple : regarder la télévision). La plupart de ces activités nécessite l'utilisation d'équipements qui consomment de l'énergie (électricité et eau). La façon dont un ménage exerce des activités est directement influencée par

les habitudes et mode de vie de ses individus ainsi que leurs préférences personnelles (par exemple : utilisation d'appareils, les niveaux d'éclairage, les préférences de température intérieure etc.) Dans cette perspective, les variables du ménage telles que la taille, la composition, l'âge et les revenus doivent être pris en compte dans le modèle.

Afin de mieux représenter les consommations d'énergie dans un bâtiment résidentiel, nous proposons une structure systématique de répartition (breakdown) sur trois niveaux (Figure 2). Au premier niveau (niveau bâtiment), nous classons les consommations d'énergie occasionnées par les systèmes inhérents au bâtiment, telles que le chauffage et le refroidissement. A ce niveau, la consommation d'énergie est principalement influencée par des déterminants liés à l'environnement et aux propriétés physiques de la construction. Les deuxième et troisième niveaux représentent la consommation d'énergie liée aux activités des occupants et de leurs appareils électro-domestiques. Au niveau intermédiaire (deuxième niveau), nous classons la consommation d'énergie qui dépend à la fois des occupants et du bâtiment. Ces consommations d'énergie ne sont pas nécessairement intentionnelles, mais peuvent plutôt être dues à la présence d'occupants à la maison (utilisation de la lumière par exemple). Au niveau de l'occupant (troisième niveau), nous classons la consommation d'énergie qui est directement liée aux activités quotidiennes intentionnelles des occupants comme la cuisine et la lessive.

Actuellement, les consommations énergétiques au niveau du bâtiment (premier niveau) bénéficient d'une bonne compréhension ; des règlements et des documentations internationales sont d'ailleurs mises en place. Les consommations d'énergie à ce niveau sont donc modélisées et simulées à l'aide d'outils de simulation énergétique avec une bonne précision. Cependant, l'utilisation de l'énergie sur les autres niveaux (niveaux 1 et 2) est encore moins explorée. Cela est dû aux difficultés relatives à la caractérisation de la variabilité de profils des occupants sur leurs comportements. Pour ces raisons, dans ce travail de recherche, nous nous concentrons principalement sur la modélisation de l'utilisation de l'énergie au troisième niveau où le comportement des occupants est prédominant et manifeste ainsi une grande variabilité. A ce niveau, la consommation d'énergie peut être représentée par les activités domestiques des occupants. Ce n'est que récemment que la notion d'« activité » a été introduite dans les modèles de consommation d'énergie résidentielle. Certaines études ont identifié les principales activités domestiques consommatrices d'énergies et développé ce que l'on appelle des modèles « basés sur

l'activité » ou Activity-based models en anglais (Kashif et al. 2011; Widén & Wäckelgård 2010; Muratori 2012).

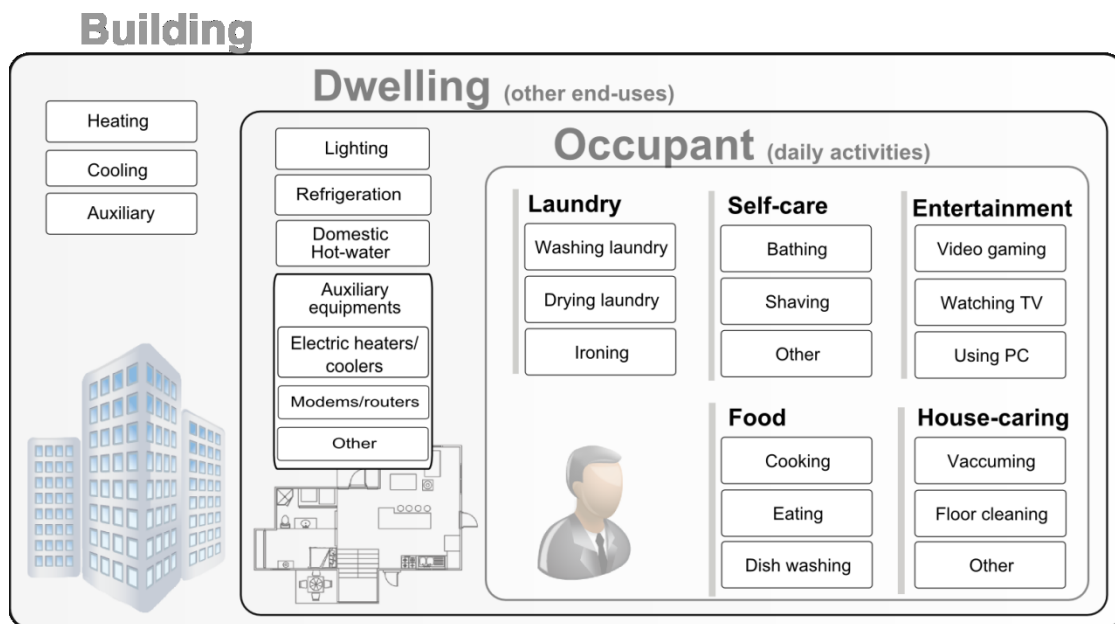


Figure 2 : Structure systématique de répartition de la consommation d'énergie dans les bâtiments résidentiels

Dans la littérature, plusieurs auteurs soulignent la présence de fortes corrélations entre les attributs d'un ménage d'un côté et le taux de possession des appareils domestiques, leur classe énergétique et leurs modes d'utilisation de l'autre (Crioc 2009; Yun & Steemers 2011; Chiou 2009b). Certains chercheurs soulignent que les approches stochastiques statistiquement dérivées constituent une bonne méthode pour simuler les comportements réels de consommation des occupants de bâtiments avec plus de précision (Fischer et Kunz, 2004; Subbiah, 2013).

Compte tenu de ces constats, nous adoptons donc une approche stochastique basée sur l'activité (SABEC : Stochastic Activity Based model of Energy Consumption) afin de modéliser les consommations d'énergie des occupants. Une approche basée sur l'activité signifie que la consommation totale d'énergie d'un ménage est estimée en sommant les consommations énergétiques individuelles des différentes activités exercées. Les quantités d'activités sont définies en fonction des attributs du ménage, puis traduites en valeurs de consommation d'énergie. En outre, la nature stochastique du modèle est due à la cartographie probabiliste établie entre les attributs du ménage d'une part (le type de ménage, nombre d'occupants etc.) et la

possession d'appareils électro-domestiques, leurs caractéristiques et la puissance et les quantités d'activité d'autre part. Afin d'établir ces relations probabilistes, un nombre assez suffisant d'attributs caractérisant des occupants est pris en compte.

D'abord, nous avons identifié les principales activités au niveau de l'occupant en intégrant leurs appareils électro-domestiques correspondants. Une classification des activités en fonction de leur nature est également établie. Une activité peut être « partagée » par deux ou plusieurs personnes (par exemple regarder le téléviseur et manger) ou « additive » où il n'y a pas de partage de l'activité entre les individus. La structure du modèle SABEC est représentée dans la Figure 3, où ses différents objets sont expliqués. A partir des attributs spécifiques d'un ménage, le modèle génère la distribution de la consommation d'énergie correspondant à une activité donnée.

Une liste de variables a été établie pour représenter les attributs des individus et des ménages (Table 1). Le choix de ces variables est basé sur la littérature et les études statistiques françaises.

Table 1 : Liste des attributs représentant un individu et un ménage

Attributs d'un individu	Attributs d'un ménage
Age	Type de ménage
Sexe	Nombre d'adulte
Statut d'activité	Nombre d'enfants
Classe socio-professionnelle	Revenu total du ménage
Niveau d'éducation	Age de la personne de référence
Revenu	Statut d'activité de la personne de référence
	Classe socio-professionnelle de la personne de référence
	Niveau d'éducation de la personne de référence

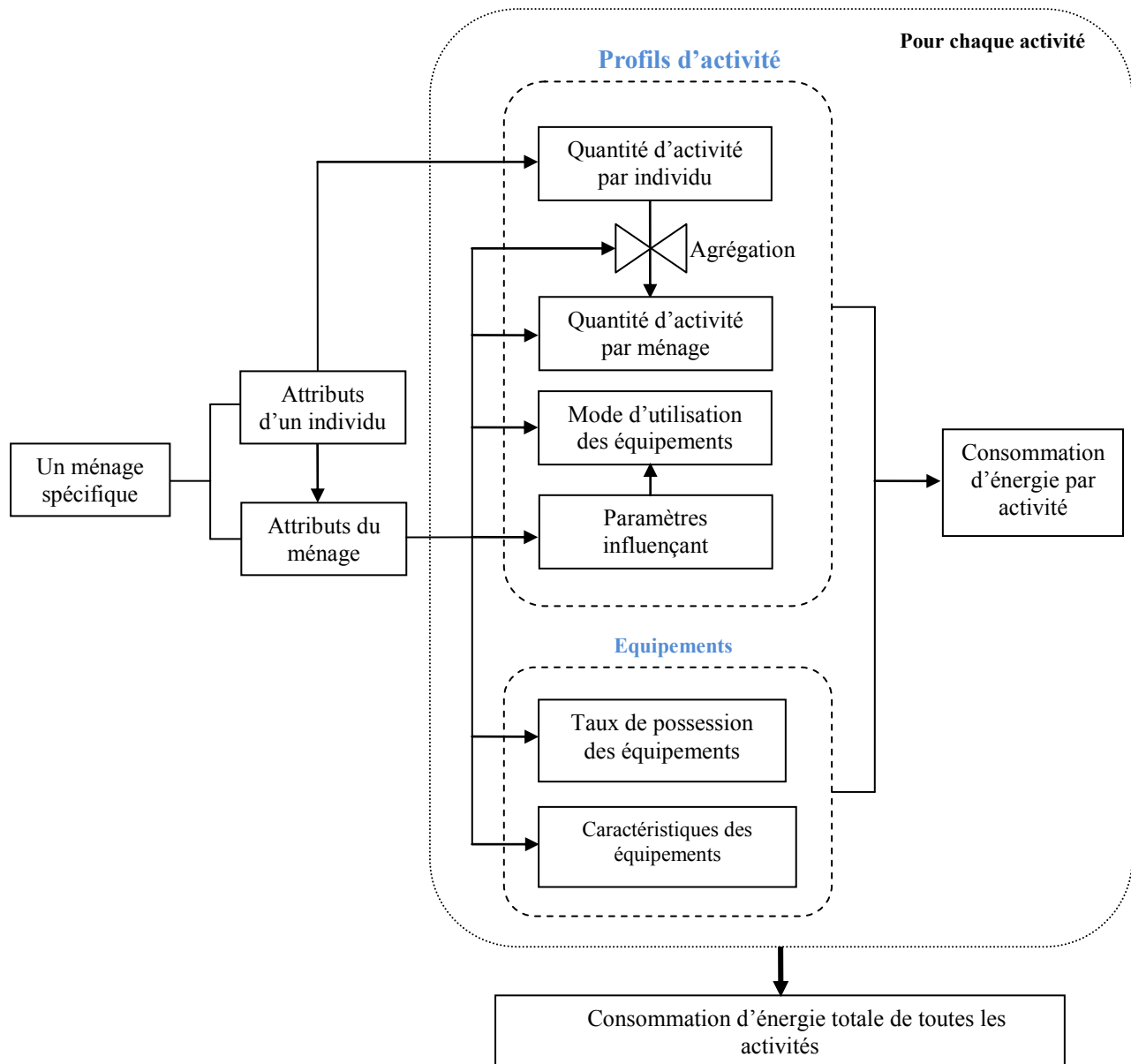


Figure 3 : Architecture du modèle SABEC

Un ménage hérite des attributs de ses occupants, par exemple, le nombre d'adultes et d'enfants ou le revenu total. Pour autant, certains de ces attributs (tels que le statut d'activité et la classe socio-professionnelle) sont ceux de la personne de référence. Cette dernière est définie comme étant la personne active la plus âgée d'une famille. La distribution de population pour chacune des variables considérées est extraite de statistiques nationales françaises.

En plus de ces caractéristiques fondamentales, certaines caractéristiques sociologiques peuvent être introduites pour représenter le comportement de la consommation d'énergie d'un ménage. Dans notre modèle, nous introduisons la variable « sensibilité écologique » dont l'influence sur la consommation d'énergie a été démontrée. Une étude nationale a qualifié la « sensibilité écologique » d'un ménage en fonction du revenu, du niveau d'éducation et de l'âge de la personne de référence (Maresca et al. 2009). La même étude révèle également que cette variable est un facteur déterminant de la classe énergétique des appareils électro-domestiques possédés par les ménages français.

La deuxième partie du modèle consiste à établir des relations entre les attributs des ménages exposés ci-dessus, le taux de possession des appareils électroménagers et leurs caractéristiques (classe énergétique, technologie etc.). Pour ce faire, des données statistiques nationales sont utilisées. Nous considérons que le taux de possession d'un appareil dépend de trois variables principales à savoir le type de ménage HH_{Type} , l'âge de la personne de référence AG_{RP} , et la classe socio-professionnelle de la personne de référence SPC_{RP} . La probabilité conditionnelle d'avoir un appareil donné, connaissant chacune de ces trois variables indépendamment, est extraite de statistiques nationales françaises (INSEE 2010). Par conséquent, la probabilité conjointe pour un ménage de posséder un appareil, $P(AP)$, peut être estimée comme indiqué dans l'Equation 1.

$$P(AP) = P(AP | HH_{type}, SPC_{HH}, AG_{RP}) \quad (1)$$

Nous considérons que la possession d'appareils économes en énergie (A et A+) est influencée par trois facteurs principaux : l'âge de la personne de référence AG_{RP} , le revenu du ménage I_{HH} et le niveau de la « sensibilité écologique » du ménage EAL_{HH} . La probabilité conditionnelle d'avoir un appareil économe en énergie connaissant chacune de ces variables indépendamment est également extraite de l'étude CREDOC de Maresca et al. (2009). Par conséquent, la probabilité conjointe pour un ménage de posséder un appareil économe en énergie $P(EAP)$, peut donc être estimée comme indiqué dans l'Equation 2.

$$P(EAP) = P(EAP | AG_{RP}, I_{HH}, EAL_{HH}) \quad (2)$$

D'autre part, la qualité ou la technologie des appareils domestiques est liée aux attributs des ménages (Morley & Hazas 2011). Toutefois, en raison de l'indisponibilité de ces informations

statistiques pour les appareils domestiques en France, nous n'avons pas tenu compte de ces corrélations dans le modèle. Cependant, pour pallier ce manque d'information, nous avons utilisé les statistiques nationales relatives aux types d'appareils et à leurs technologies présentes dans les logements français.

Afin de quantifier une activité donnée, la notion d'« unité de service » est adoptée. Sa définition est basée sur celle de l'unité fonctionnelle utilisée en Analyse de Cycle de Vie (ACV). L'unité de service (US) est une mesure de la quantité d'activité réalisée sur un temps donné. Par exemple, l'unité de service de l'activité « manger » est définie comme étant le nombre de repas consommés par jour. La proposition de cette approche basée sur les activités repose sur deux grandes hypothèses. D'une part, nous considérons et définissons les activités pour qu'elles soient additives (elles ne se « recouvrent » pas) et donc que la consommation totale d'énergie par ménage au niveau de l'occupant est égale à la somme des consommations d'énergie de toutes les activités (voir Figure 2). D'autre part, la quantité totale d'une activité par ménage est dérivée selon sa nature : si l'activité est additive, l'unité de service total est la somme des unités de service pour chaque individu ; et si elle est partagée, une fonction d'agrégation doit être définie pour prendre en compte la partie de partage pour l'estimation de la quantité totale d'activité.

Une caractéristique importante d'un tel modèle d'activité est la « **cascade d'unités de service** » où l'unité de service d'une activité peut être utilisée pour quantifier d'autres activités connexes. Par exemple, l'US pour l'activité « séchage du linge » peut être déduite de celle de l'activité « lavage du linge » en ajoutant certaines modulations en fonction des caractéristiques du ménage. Cette cascade d'unités de service peut donc faciliter l'estimation de la totalité d'unités de service pour toutes les activités et éventuellement l'estimation de la consommation d'énergie de ces activités.

La consommation d'énergie d'une activité pour un ménage donné est donc estimée en fonction de toutes les variables précédemment exposées. Compte tenu de la nature probabiliste de notre modèle, la méthode de Monte Carlo est utilisée pour l'exécution des simulations. Pour chaque cycle de simulations, une combinaison différente de variables est générée et donc différentes valeurs de consommation sont obtenues. Le nombre d'itérations est défini en fonction de la convergence des résultats. Au cours de chaque simulation, les variables aléatoires sont générées pour calculer : (1) le taux de possession des équipements, (2) le niveau de sensibilité écologique

du ménage, (3) l'efficacité énergétique des équipements et (4) la technologie des équipements. L'énergie consommée par une activité et pour un ménage donné AEC_{HH} , est ainsi calculée de manière stochastique en fonction de l'unité de service de l'activité ASU_{HH} et de la puissance P de l'équipement utilisé, comme indiqué dans la Figure 4. La consommation finale d'énergie générée par une activité est donc estimée comme indiqué dans l'Equation 3 :

$$AEC_{HH} = W \times F \times P \times ASU_{HH} \quad (3)$$

W représente la possession d'un appareil et il est déterminé par la génération d'une variable aléatoire intermédiaire R_2 . F représente le rendement énergétique de l'appareil et il est déterminé par la génération d'une variable aléatoire intermédiaire R_3 . ASU_{HH} est l'unité de service totale du ménage et P est la puissance consommée par l'appareil qui est choisi au hasard à partir des intervalles de puissance provenant de données statistiques ($P = P_1$ pour le mode ON et $P = P_2$ pour le mode veille).

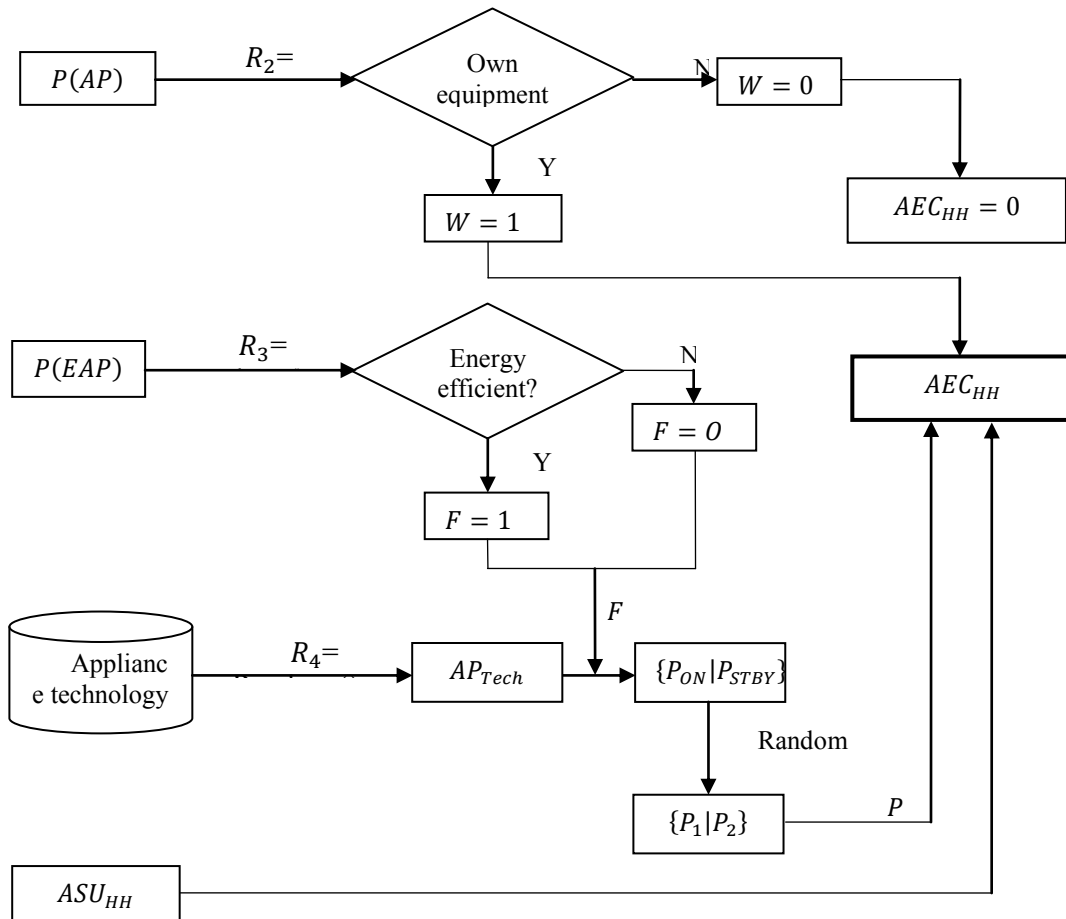


Figure 4 : La méthode de simulation pour calculer la consommation d'énergie pour une activité

Le modèle SABEC proposé est ensuite appliqué sur deux activités domestiques, à savoir « regarder la télévision » dans le chapitre 4 et « laver le linge » dans le chapitre 5. L'application du modèle SABEC est réalisée pour (1) tester les fonctionnalités du modèle et sa capacité à simuler la consommation d'énergie des activités domestiques, (2) révéler les difficultés de modélisation telles que le choix des variables déterminantes de l'activité et la quantification des unités de service des activités et (3) valider le modèle en comparant ses résultats de simulations à des données réelles.

Pour cette raison, le modèle a été mis en œuvre en langage Python et une interface graphique simplifiée de l'utilisateur a été développée. Il est à noter que le modèle est construit de manière à fournir différents types de simulations. Nous pouvons par exemple simuler la consommation d'énergie pour un ménage spécifique. Les différents attributs tels que le type de ménage, le revenu, l'âge et le sexe des individus peuvent être spécifiés. Le modèle permet également d'exécuter des simulations pour un échantillon aléatoire de ménages. Pour ce type de simulation, les ménages choisis au hasard sont représentatifs de la population française. Enfin, il est possible de définir des contraintes sur un ou plusieurs des attributs du ménage. Par exemple, nous pouvons choisir de ne simuler que des ménages d'une certaine catégorie socio-professionnelle, d'un certain type (famille mono-parentale par exemple), ou même d'une certaine classe de revenu.

Compte tenu de la nature probabiliste de notre modèle, la méthode de Monte Carlo est utilisée pour l'exécution des simulations. Pour chaque cycle de simulation, une combinaison différente de variables est générée et donc différentes valeurs de consommation sont obtenues. Le nombre d'itérations est défini en fonction de niveau de convergence des résultats.

Afin d'appliquer le modèle SABEC sur l'activité « regarder la télévision », les étapes de modélisation et simulation exposées auparavant sont utilisées (Figure 5). « Regarder la télévision » est considérée comme l'une des activités les plus consommatrices d'électricité au sein des ménages français avec une variété dans le taux de possession des téléviseurs, et les types et technologies de ces appareils. Pour modéliser cette activité nous avons identifié les différents usages du téléviseur. Les deux usages suivants ont été considérés : regarder les chaînes de télévision et des vidéos DVD. Les autres usages, comme les jeux vidéo ou la navigation internet sont à prendre en compte dans d'autres activités. Nous considérons l'activité « regarder la

télévision » comme une activité partagée. Son unité de service est définie comme étant la durée passée à regarder la télévision par personne et par jour.

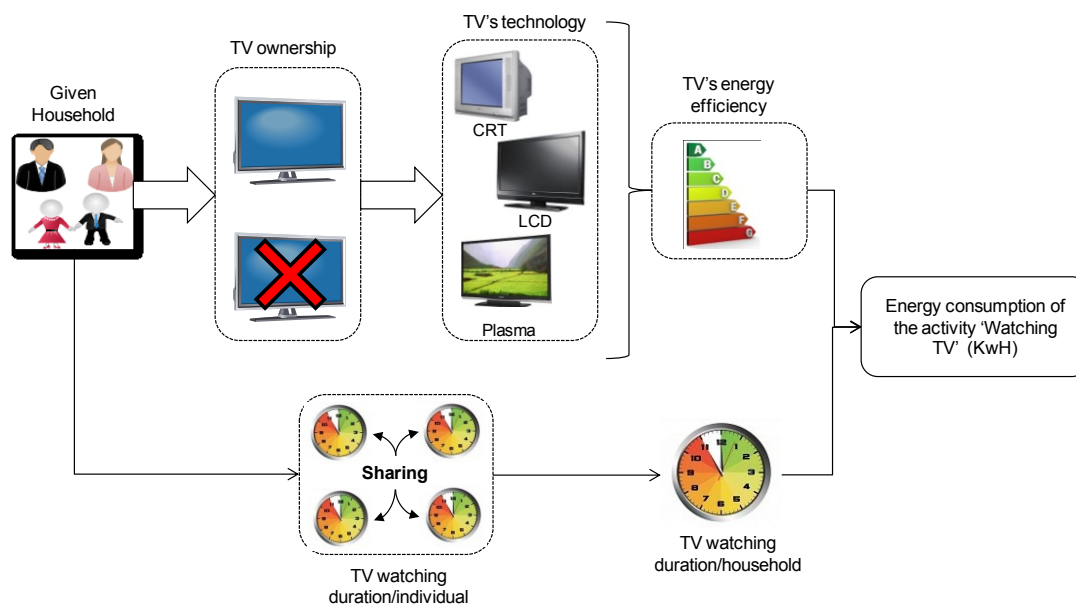


Figure 5 : Application du modèle SABEC pour l'activité « regarder la télévision »

En utilisant le cadre de modélisation SABEC, nous corrélons dans un premier temps les attributs du ménage (âge, catégorie socio-professionnelle) au taux de possession du téléviseur, à sa technologie (CRT, LCD, plasma) et à sa classe énergétique. Ces corrélations sont établies en s'appuyant sur de données statistiques nationales. L'unité de service est d'abord quantifiée par individu en utilisant des données statistiques de l'Institut National Français de la Statistique et des Etudes Economiques (INSEE). En raison de la nature partagée de l'activité, la quantité totale de l'unité de service par foyer (ASU_{HH}) est déterminée par une fonction d'agrégation qui prend en compte le taux de partage, une variable qui est directement corrélée avec le type de ménage. Ensuite, en couplant l'unité de service total avec la puissance de l'appareil, la consommation d'électricité totale par ménage peut être estimée.

Une fois le modèle établi, des simulations sont ensuite effectuées selon les différentes fonctionnalités du modèle : (1) pour des ménages spécifiques, (2) pour des ménages aléatoires avec des contraintes sur les attributs et (3) pour des ménages aléatoires représentatifs de la population française. Pour chacun de ces trois cas, les résultats de simulations sont utilisés pour évaluer et interpréter la variabilité de la consommation d'énergie entre les ménages en fonction de

leurs attributs. Enfin, le modèle est validé en testant la signification statistique des résultats de simulations par rapport aux données réelles provenant d'une étude nationale. Pour ce faire, nous utilisons les statistiques descriptives et un test statistique non paramétrique, celui de Mann Whitney-Wilcoxon.

La deuxième application concerne l'activité « laver le linge ». La principale différence entre cette activité et la précédente est sa nature additive. En outre, un plus grand nombre de variables peut influencer la quantification de son unité de service. Comme pour l'activité « regarder la télévision », nous avons établi des corrélations entre les attributs du ménage, le taux de possession des machines à laver, ses caractéristiques et ses classes énergétiques (Figure 6).

L'unité de service pour cette activité est définie comme étant la quantité de linge à laver par ménage et par mois. Nous considérons que le linge comprend les vêtements clairs, les vêtements colorés et le linge de maison (draps, serviettes etc.). Le poids des vêtements sales produits par un individu (en Kg) est défini en fonction de son âge, sa taille et son poids, tandis que la quantité de linge de maison est estimée en fonction du type de ménage. Afin de quantifier l'unité de service totale par ménage, un nombre de variables intermédiaires est également introduit, telles que le taux de changement de linge, le taux de remplissage du tambour, la température de lavage et la capacité totale de la machine à laver. En raison du manque de données statistiques nationales, une enquête en ligne a été menée auprès de 105 ménages français pour recueillir des distributions statistiques concernant certaines de ces variables.

Finalement, la combinaison de l'unité de service totale par ménage et des caractéristiques de la machine à laver (capacité, classe énergétique, ..) permet d'estimer la distribution de la consommation d'énergie pour cette activité.

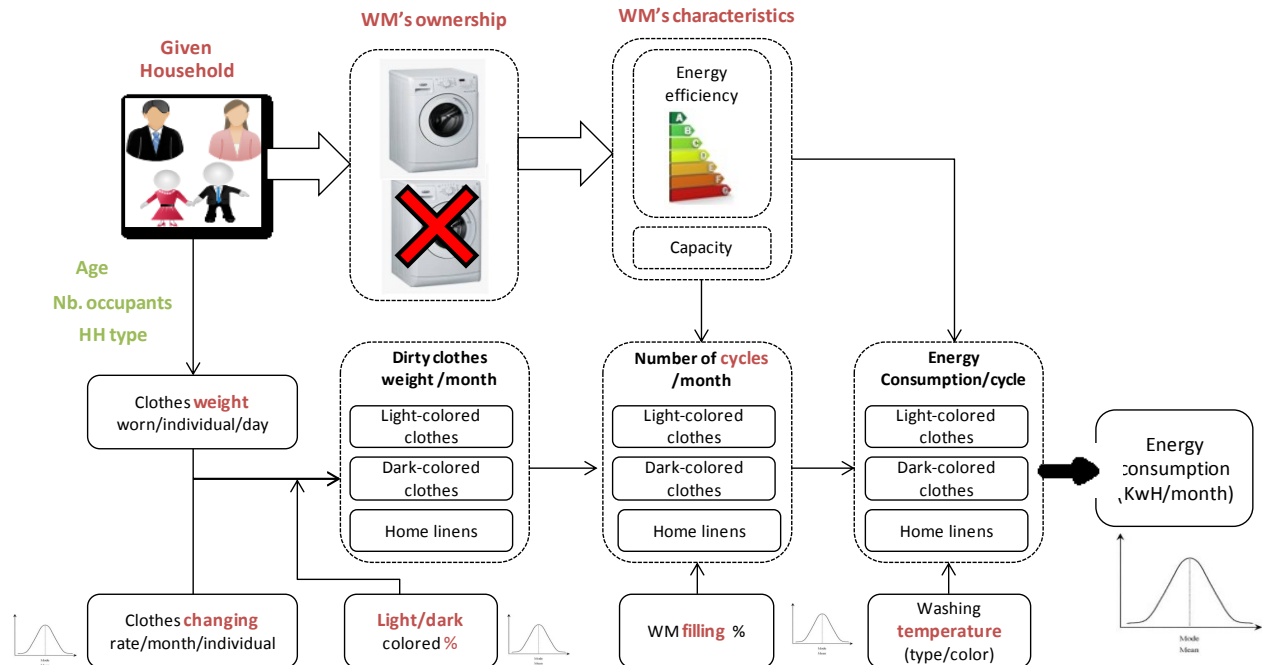


Figure 6 : Application du modèle SABEC pour l'activité « Laver le linge »

Une fois le modèle établi, des simulations sont ensuite réalisées selon les différentes fonctionnalités du modèle. Pour chacun des trois types de simulations, les résultats sont utilisés pour évaluer et interpréter la variabilité de la consommation d'énergie entre les ménages. Enfin, le modèle est validé en testant la signification statistique des résultats de simulations par rapport aux données réelles provenant d'une étude nationale (Enertech 2008). La comparaison des résultats de simulations est faite seulement pour la consommation d'électricité. Les résultats de la consommation d'eau ne sont pas confrontés à des données réelles en raison de la non-disponibilité de données fiables. Ceci sera fait une fois que les données manquantes auront été collectées.

Une fois le modèle développé et appliqué sur deux activités, différentes questions sont abordées pour le généraliser et le rendre opérationnel dans un contexte industriel. Afin de généraliser le modèle à d'autres activités domestiques, des métarègles ont été définies. Il faut d'abord identifier les différents processus et actions de l'activité. Ceux-ci sont notamment caractérisés par les appareils mobilisés et par les flux d'énergie consommés. Par la suite, les variables les plus influentes sont identifiées et corrélées aux attributs du ménage via des distributions de probabilités.

Dans un deuxième temps, nous avons abordé la question de la simplification du modèle afin de le rendre le plus parcimonieux possible. Une application de simplification a été réalisée pour le modèle de l'activité « laver le linge ». Une étude de sensibilité est effectuée pour identifier les variables les plus impactantes. Nous avons mis en évidence que les facteurs les plus importants liés aux occupants sont le nombre d'adultes et le nombre d'enfants par ménage, ainsi que le revenu total du ménage. Ensuite, un modèle simplifié de cette activité est proposé sur la base de ces variables. Une comparaison entre les résultats de simulations des deux modèles, simplifié et raffiné, est réalisée et discutée.

A la fin de cette thèse, une partie est consacrée afin d'investiguer les différentes possibilités d'intégration du modèle SABEC dans le contexte industriel. Le modèle proposé peut être utilisé comme un outil complémentaire aux outils de simulation énergétique traditionnellement utilisés. Il peut fournir des prévisions plus précises de consommations d'énergie par ménage et par activité. Ces prévisions énergétiques précises peuvent ainsi être utilisées pour guider le raffinement des garanties de performance énergétique (proposée par le constructeur) en définissant des seuils de consommation plus précis. En outre, le modèle peut être utilisé pour tester des alternatives de conception fortement dépendantes du comportement des occupants (par exemple une buanderie commune au sein d'une résidence équipée de machines à laver très économes en énergie).

Le modèle SABEC proposé peut aussi être éventuellement utilisé pour enrichir des outils intelligents utilisés pour la surveillance de la consommation d'énergie résidentielle. Par exemple, si les principaux usages de consommation d'énergie sont identifiés, les experts du bâtiment peuvent installer des capteurs intelligents supplémentaires pour mesurer et suivre ces consommations. En outre, les occupants peuvent avoir des informations plus détaillées sur leur consommation d'électricité et d'eau pour chaque activité domestique et peuvent donc être incités à limiter leurs consommations. Enfin, grâce à des outils connectés, les constructeurs pourront un jour être en possession de données pertinentes et détaillées concernant les consommations d'eau et d'électricité au cours de la phase d'utilisation du bâtiment, en fonction des profils de ménages. Par conséquent, ils pourront également utiliser ces informations afin d'améliorer les solutions de conception de nouveaux bâtiments, ainsi que pour proposer de nouveaux services aux occupants.

A l'issue de cette thèse, un nombre de perspectives sur la poursuite des travaux a été identifié. Dans un premier temps, nous comptons étendre l'approche de modélisation à toutes les autres activités domestiques consommatrices d'énergie. Dans un second temps, nous travaillerons sur la simplification du modèle afin de le rendre le plus parcimonieux possible. Par la suite, nous devons valider le modèle global de simulation de consommations énergétiques en le recalant à des données statistiques disponibles ou à des données mesurées in situ. Enfin, le modèle a vocation à être développé au sein d'une plateforme informatique de simulation énergétique des activités des occupants. Cet outil a pour ambition d'être industrialisé et intégré dans le processus de conception de bâtiments résidentiels.

Chapter 1: Introduction

1.1 Background and motivation

The buildings sector is considered as a major energy consumer and pollution source in most countries. Buildings account for important shares, ranging between 16 and 50 percent, of national energy consumption worldwide (Masoso and Grobler, 2010; Saidur et al., 2007). In France for instance, the building stock uses up to 43% of total national energy consumption and engenders about 25% of total CO₂ emissions (ADEME, 2012a). In recent years, it has come to light that buildings sector in France may be the only one, among other industrial sectors, capable of making a significant progress for meeting national commitments towards reducing greenhouse gas emissions. Reducing and controlling energy consumption and environmental impacts of buildings are thus a critical challenge for governments and building experts.

Similarly to other developed countries, French authorities have established recently a number of standards and regulations so as to promote sustainable development in the building sector. The latest French thermal regulation which defines performance standards of buildings is the RT 2012, standing for “Réglementation Thermique 2012” (i.e. Thermal Regulation). This regulation is an ambitious step towards promoting green buildings since it plans to divide by three the energy consumption of new buildings starting from the end of year 2012. As a result of such regulations, building constructors are tending more and more to construct energy-efficient and green buildings. Moreover, a so-called “Energy performance guarantee”, which is a performance commitment between building constructors and owners, is a new market expectation emerging in France (CPE, 2012). By this contract, constructors commit to deliver an eco-efficient building and to guarantee this performance threshold (measured in MWh and transformed into Euros) for a certain number of years after handover. This shift towards constructing low-consuming and nearly zero energy buildings, leads to further requirements of performance and sustainability and thus causes the design process of buildings to be more and more complex. Therefore, a better comprehension and integration of building performance determinants into the design of buildings, especially in the very early phases, has become essential.

In general, the energy performance of a building is governed by various factors, such as its physical characteristics (e.g. surface area and orientation) its internal services systems (e.g. heating and ventilation systems) and equipments (e.g. lighting), its external environment (e.g. temperature and humidity) and most importantly its occupants (Fabi et al., 2012; Yu et al., 2011). Past experience points out the substantial role of occupants in influencing buildings' performance, and classifies occupant behavior as a key determinant of building-energy consumption (Clevenger and Haymaker, 2006; Swan and Ugursal, 2009). The influence of occupants on the building can be modeled by their presence and the actions they perform (activities such as cooking, washing, etc.), as well as their interactions with the controls of building systems used for adjusting indoor environment variables (e.g. changing thermostat setting-temperature for thermal comfort, adjusting lighting intensity for visual comfort, etc.) (Page et al., 2008; Robinson, 2006; Yu et al., 2011).

In spite of their importance, occupants have not been considered as decision parameters in building energy simulation tools until recently (Chiou, 2009a; Malavazos et al., 2011). In fact, simulation tools used by building designers and experts nowadays, focus primarily on the structural behavior of buildings and their relations to specific environmental conditions while taking insufficiently into account the role of the occupants in the system in use. Due to the complexity in capturing user preferences and energy consumption patterns, existing simulation tools tend to eliminate the influence of users as far as possible to optimize building performance (Chiou, 2009a; Page et al., 2008). Actually, such tools consider occupants as monolithic elements with standard and averaged energy use patterns and consumption profiles. Consequently, energy performance predictions yielded by these tools can deviate dramatically from reality (Kashif et al., 2012; Malavazos et al., 2011).

For these reasons, energy and buildings experts have started recently devoting considerable efforts to finding tools, techniques and approaches that enable them to better understand and interpret complex energy consumption phenomena within buildings. Large efforts are focused on developing more precise methods for modeling occupants influence on buildings' energy performance. A number of researchers highlight that statistically derived stochastic approaches provide a good methodology to simulate real consumption behaviors of buildings' occupants more accurately (Fischer and Kunz, 2004; Subbiah, 2013).

Such models should result in more accurate energy estimation results, and thus in better building designs. By this, we mean that designers could have the ability to improve their technical solutions, making them more independent of usage variability by, for instance, installation of movement sensors, or automatic disconnection of lighting equipments in case of non-use. In addition, energy consumption estimations would be more accurate, service performances would be more guaranteed and appropriate and targeted incentives could be proposed.

1.2 Research context

The present research work is conducted in collaboration between BOUYGUES Construction and the Industrial Engineering Laboratory (Laboratoire Génie Industriel, LGI) at Ecole Centrale Paris. Thus, our research objectives were defined in a way to comply with both industrial and academic perspectives.

1.2.1 Industrial context

The interest manifested by our industrial partner into this research can be placed in the scope of sustainable development or, more precisely, the eco-design of residential buildings. In fact, BOUYGUES construction is a pioneer actor in constructing green buildings (Bâtiment Basse Consommation or BBC) in France.

Building experts rely on energy simulation tools in order to assess building's future performance. Simulation results yielded by these tools are used for guiding building designs so that to comply with national energy performance regulations. Moreover, these simulations are used by building constructors for refining offers such as energy performance guarantees and maintenance services. However, due to their shortcomings with regard to capturing occupants' consumption patterns, existing energy simulation tools cannot provide accurate energy estimates. Consequently, building constructors are in need for powerful simulation tools capable of providing more precise energy demand estimations. This need is manifested particularly for the case of newly constructed green buildings. According to our industrial partner, integrating such tools into the design phase of buildings can thus be of great interest.

1.2.2 Academic context

The research work conducted in this thesis takes place within the Design Engineering team of the Industrial Engineering Laboratory at Ecole Centrale Paris. The research team objective is to model, analyze and design complex systems: products, design processes and designing organizations. Several models of usage modeling have been developed like the Usage Coverage Model in (Yannou et al., 2013) and (Wang, 2012), but also in (Cluzel et al., 2013; Picon et al., 2013).

Given this academic context, the work of the present thesis falls thus into two main research streams. The first stream is the modeling of usage contexts for products and services. In our case, the product is represented by residential buildings and the users are thus their occupants. The usages are in this case represented by energy consumption behaviors and activity patterns of buildings' occupants. Here it is more accurate to speak of activity instead of usage, since neither the usage contexts nor the usage motivations will be studied but only the quantities of energy-consuming activities. The second stream is related to the integration of eco-design into industrial contexts. Indeed, developing tools and models that aid reducing energy consumption in residential buildings is at the heart of sustainable development and eco-design paradigms.

1.3 Objectives and research questions

The objective of this research work is to develop a parametric predictive model for forecasting occupant-related energy consumption in residential buildings. The major aims intended through the model are:

- First to provide realistic and accurate predictions of energy consumption at a very fine granularity (at the level of domestic activities).
- Second to provide energy estimates disaggregated to the level of households and individuals as a function of their socio-demographic and economic attributes.
- Third to be able to assess the variability in energy consumption between different individuals and households with different attributes (different occupant profiles).

The examination of both industrial and research contexts, and the review of literature at the beginning of the thesis (see chapter 2 for detailed literature review) enabled us to formulate three major research questions that are exposed hereafter.

Question 1

Is it possible to depict, characterize and model energy consumption in residential buildings through an activity-based approach?

Most researchers agree that the energy use is embedded in most aspects of daily life. People use energy to satisfy certain daily living activities such as preserving and preparing food, supplying heat and light, and maintaining health and sanitation. The notion of daily-living activities is employed in several manners depending on authors' objectives and their scope of study. An activity-based model may thus be an important step towards understanding, representing, and characterizing occupant-related energy consumption in residential buildings.

Question 2

How to model and simulate energy consumption in residential buildings while accounting for the variability of household profiles as well as the stochastic nature of domestic activities and equipment possession?

Energy consumption can vary dramatically between different households. This variation is due to the difference in occupant profiles that has each its own consumption figure. The socio-demographic and economic characteristics of occupants can impact their possession probabilities of domestic appliances as well as their living and consumption patterns. Therefore, accounting for this consumption variability is very substantial.

Question 3

Is it possible to integrate “energy consumption models per household profile” into the design process of buildings, and how such models can be used in the perspective of improving the robustness of building’s energy performance?

A model which provides precise forecasting of occupant-related energy consumption is highly appreciated by building experts. The integration step of such modeling approach into the industrial context is thus primordial. Therefore, a detailed description of this possible integration and future possible applications of the model is needed.

1.4 Research outcomes

In this work, we develop a stochastic activity-based energy consumption model. By activity-based, it means that energy consumption of a household is estimated by summing up the energy use of different activities performed (such as cooking, washing clothes, etc.). The stochastic nature of the model is due to the probabilistic mapping established between household attributes from one side (household type, number of occupants, etc.) and the corresponding appliance ownership, appliance characteristics and power rating, and activity quantities from the other side. Statistically-derived data are used to establish this probabilistic mapping. A fairly sufficient number of households' characterizing attributes is taken into account based on literature review and statistical studies.

The proposed model is applied for two domestic activities, namely watching TV and washing laundry. Three types of Monte Carlo simulations are performed to provide energy estimates for these two activities: for a given specified household, for randomly generated households with constraints, and for totally random population-wise households. A comparison between model's simulation results and real measured energy consumption data enables validating the model for the two considered activities. A generalization framework of the modeling approach for other domestic activities is sketched, and its possible integration into buildings design process is discussed and illustrated through a number of examples.

1.5 Dissertation organization

This dissertation comprises 6 chapters. The organization of chapters is described below and illustrated through Figure 1.1.

Chapter 1: Introduction—this chapter provides an introduction on the background and motivation of our research work, its objectives and the organization of the dissertation.

Chapter 2: Literature review—this chapter provides a structured literature review relevant to the defined research context.

Chapter 3: Stochastic activity-based approach for modeling occupant-related residential energy consumption—this chapter details the development of the proposed Activity-Based energy consumption model.

Chapter 4: Application of SABEC¹ model for the domestic activity “Watching TV”.

Chapter 5: Application of the SABEC model on the domestic activity “Washing laundry”.

Chapter 6: Generalization of the modeling approach and its possible integration into the industrial context of residential buildings — this chapter tackles various issues for generalizing the modeling and simulation method and making it practically usable in a professional context.

¹ Stochastic activity based energy consumption model

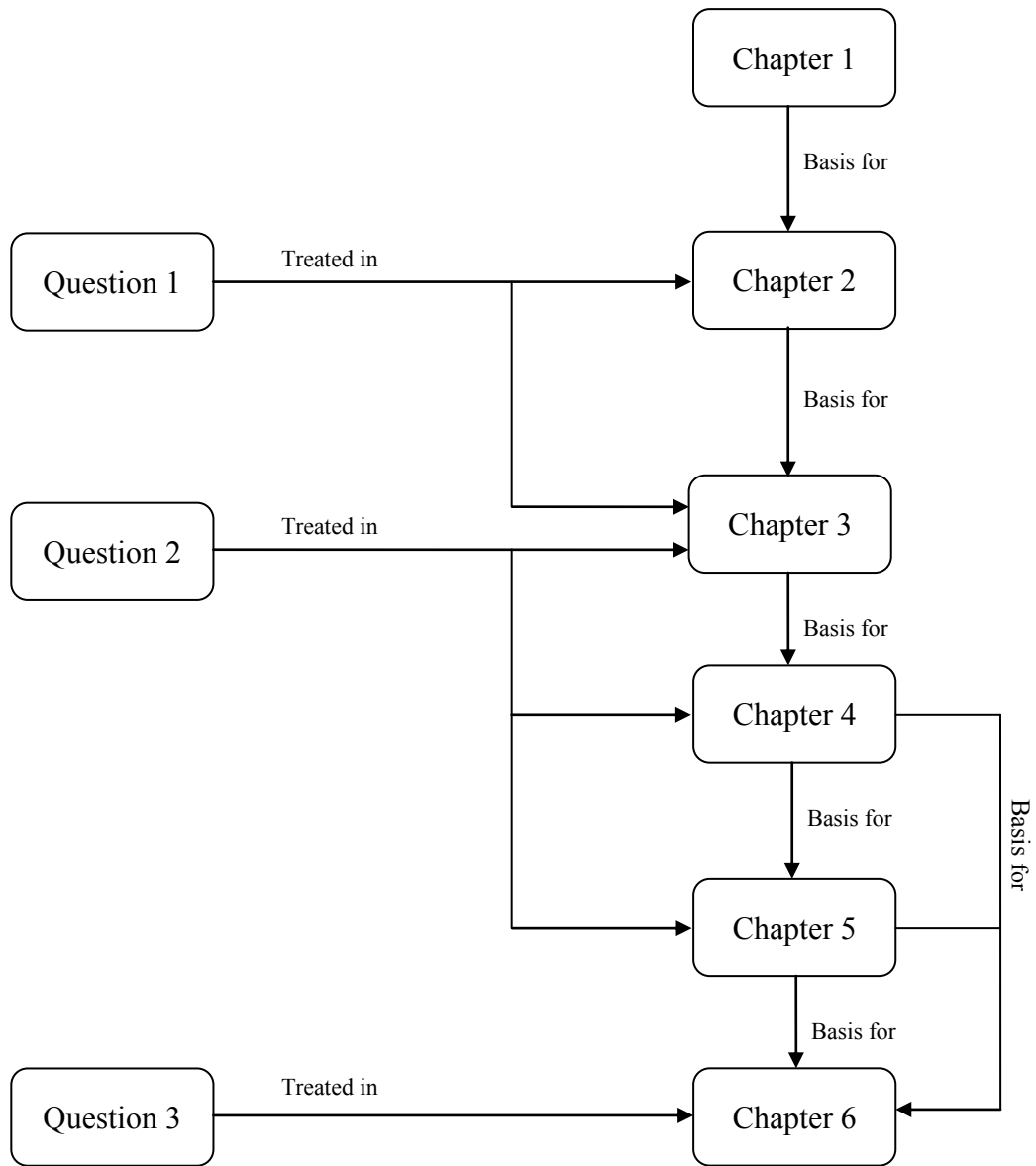


Figure 1.1: Dissertation organization

Chapter 2: Literature review

2.1 The building sector: an important energy sink

The buildings sector is a substantial energy consumer among industrial sectors. It accounts for important shares, ranging between 16 and 50 percent, of national energy consumption worldwide (Hoes et al., 2009; Masoso and Grobler, 2010; Saidur et al., 2007). In France, the building sector is the highest energy consumer among industrial sectors (ADEME, 2012a). It uses up to 44% of the total national energy consumption right ahead other major sectors such as transportation, industry, steel industry and agriculture (Figure 2.1). Moreover, French buildings engender 25% of total national CO₂ emissions (ADEME, 2013). As shown in Figure 2.1, buildings thus represent the major source of consumption of energy in France, with 70% for residential and 30% for tertiary buildings.

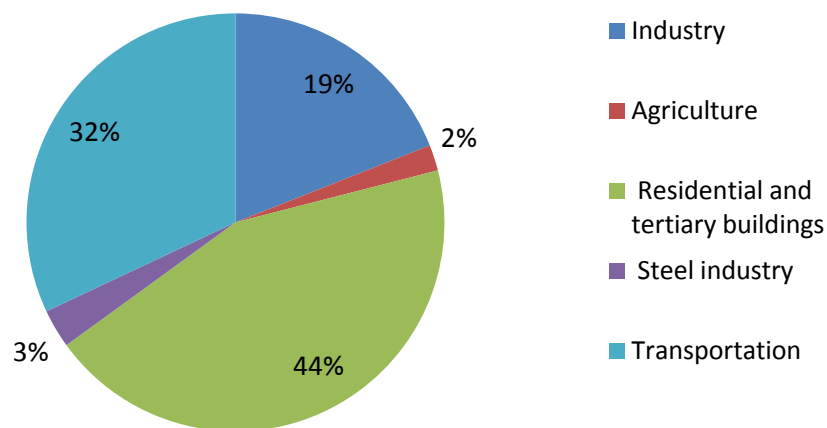


Figure 2.1 : Energy consumption share per each sector in France (ADEME, 2012a)

Therefore, the residential buildings stock in France is considered as a huge reservoir of energy savings and a main actor in reducing greenhouse gas emissions. Building occupants in their turn are considered as important actors who must be incited to change their consumption behaviors. Given the scale of the challenge, an ambitious action plan is being implemented at the national level to: increase the mobilization of all building actors, to define more restrictive regulatory

measures, to provide financial incentives for households, to offer significant financial support to building owners, and also to support research and development projects.

Reducing these consumptions and emissions is therefore an important step towards sustainable development. The French authorities established recently a number of standards and regulations so that to meet national commitments with regard to reducing greenhouse gases. The latest French thermal regulation which defines performance standards of buildings is the RT 2012, standing for “Réglementations Thermiques 2012” (i.e. Thermal Regulation). This regulation is an ambitious step towards promoting green buildings since it plans to divide by three the energy consumption of new buildings starting from the end of year 2012.

2.2 Energy consumption in residential buildings: an overview

2.2.1 Energy end uses

During last years, the construction of green and energy-efficient buildings has been accompanied with a great interest in exploring and understanding more accurately the energy consumption phenomena within residential buildings. Authors such as Swan and Urgusal (2009) conclude that the energy consumption of the residential sector is still ambiguous and not well understood, whereas for other sectors such as commercial, industrial, agriculture and transportation, a good understanding has been established and high levels of regulation and documentation have been established. These authors define the residential sector as an undefined energy sink due to the following reasons:

- The sector encompasses a wide variety of structure sizes, geometries and thermal envelope materials.
- Occupant behavior varies widely and can impact energy consumption by as much as 100% for a given dwelling (Seryak and Kissock, 2003).
- Privacy issues limit the successful collection or distribution of energy data related to individual households.
- Detailed sub-metering of household end-uses has prohibitive cost.

Residential edifices consume secondary energy, which is used by occupants in suitable forms for their daily livings. A number of authors such as Hoes et al. (2009), Yao & Steemers (2005), Tso (2003), and Swan & Ugursal (2009), pointed out the major end-use groups of secondary energy in residential buildings. These groups can be broken down as following:

- Space heating and space cooling: energy required to support thermal losses incurred across the building envelope due to conduction and radiation, as well as air infiltration/ventilation in an effort to maintain the living space at a comfortable temperature and air quality.
- Domestic hot water: energy required to heat water to a comfortable or appropriate temperature for occupant and appliance uses.
- Appliances and lighting: energy consumed to operate common appliances (e.g. refrigerator and coffee maker) and for the provision of adequate lighting.

Authors such as Chiou (2009a) conclude that operational energy use of domestic buildings can be divided into two categories of sources. The first category encompasses the energy used by indoor environmental-control devices and systems such as lighting, heating, ventilation and air conditioning (HVAC) that occupants use for adjusting their comfort level. The second category however includes the appliances that occupants use for performing their daily living activities such as cooking, washing, and entertainment.

2.2.2 The case of French buildings

In this section, we expose the energy consumption in French buildings and the way how this consumption is taken into account in national standards. In France, the average distribution of energy consumption in existing residential buildings is represented as a function of four major end uses. These are Heating, domestic hot water, cooking and specific electricity (Figure 2.2).The

main part of this consumption is used for heating which accounts for 62.1%, followed by 12.1% for hot water, 6.9% for cooking and 18.9% for specific uses² (ADEME, 2012a).

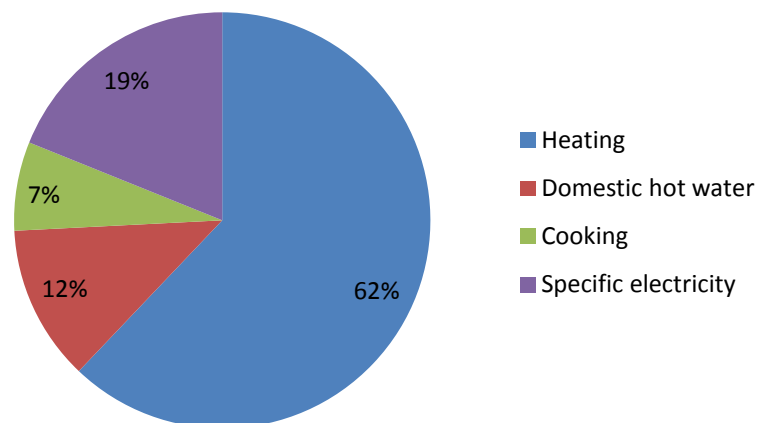


Figure 2.2 : Average distribution of energy consumption in existing residential buildings in France (ADEME, 2012a)

In recent years, French authorities have established a number of standards and regulations to limit energy consumptions of these end-uses. These regulations aimed mainly at reducing energy consumed for heating due to its large contribution. The latest thermal regulation which specifies performance standards of buildings in France, namely TR 2012, takes into account five main energy end-uses. These are heating, cooling, lighting, domestic hot water and auxiliary equipments (heat pumps and ventilators). The determination of the primary energy consumed by a building (referred to as Cep) is done by summing up the consumption of each of these five end-uses (RT 2012, 2011). According to the RT2012, a residential building can be considered energy-efficient if it does not consume more than 50 Kwh/m²/year of primary energy³ (PE). In this regulation, the average energy consumption in energy-efficient buildings is thus allocated to

² Specific electricity: electricity used by equipments that can only work with electricity and cannot work with other sources of energy. The electricity used for heating, hot water or cooking is not specific electricity, as other energy can be used.

³ Primary energy (PE): Primary energy is an energy form found in nature that has not been subjected to any conversion or transformation process (Wikipedia).

different end-uses as follows: 15 KWh/m²/year for heating and cooling, 25 for hot water, 5 for lighting and 5 for auxiliaries.

Although the TR 2012 presents a good progress towards reducing the total energy use in buildings, it is still not accounting sufficiently for the last category of end-uses, which is specific electricity. Cardonnel (2010) studies energy consumption in newly constructed buildings in France and highlights the weight of households' specific electricity usages on the overall energy consumption. This study compares dwellings' energy consumption as taken by the thermal regulation RT2012 (Cep) from one side and the real energy consumption considering specific end-uses from the other side. This comparison is illustrated in Table 2.1, where the values are given in KWh PE/year/m². As it can be concluded from this table, in contrast to the case of non-efficient buildings, heating is no more the most consuming source of energy in green-buildings. However, specific electricity end-uses are now representing a larger share of the total energy consumption with almost 60 KWh PE/year/m².

Table 2.1: Distribution of dwelling energy consumption: Comparison between conventional five end-uses defined in RT2012 (left) and the household specific end-uses (right) (Cardonnel, 2010) in KWh PE/year/m².

End-uses taken into account in RT2012		Other end-uses (not taken into account in RT2012)	
Auxiliary	5	Cooking	10
Lighting	5	Electro-domestic	25
Heating	15	Multimedia	25
Domestic Hot Water	25		
Total	50	Total	60

According to the French Environment and Energy Management Agency (ADEME), 52% of the electricity consumption of households today are due to specific electricity usage (ADEME, 2012b). The average electricity consumption of a French household excluding heating and domestic hot water is around 2700 kWh/year (ADEME, 2012b). The distribution of average specific electricity consumption per end use is presented in Figure 2.3.

This specific electricity consumption has doubled between 1985 and 2008. Although the energy efficiency of electrical equipments is steadily improving, yet the French electricity consumption is still increasing. According to the ADEME, several explanations are possible: the increasing

number of domestic electrical equipments per dwelling (entertainment equipments in particular), their size and their increasing usage duration by individuals, in addition, the non-efficient usage of these devices. For these reasons, understanding predicting and limiting specific electricity consumption became highly urgent for energy and buildings experts

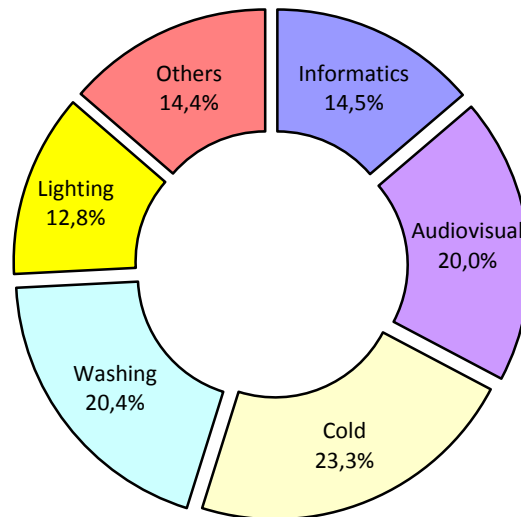


Figure 2.3: Distribution of average specific electricity consumption per end-use (ADEME, 2012b)

2.2.3 Determinants of energy consumption in residential buildings

Past literature has identified the major determinants that regulate energy consumption in residential buildings. In general, the energy performance of a building is governed by various parameters, such as its physical characteristics, its internal services systems and equipments, its external environment and most importantly its occupants (S. Pachauri, 2004; Page et al., 2008; Yu et al., 2011). Fabi et al. (2011) and (2012) conducted a literature review concerning the factors that influence occupant behaviors and their energy consumption in buildings. Based on their findings, the authors presented the general process leading from occupant behavior driving forces (drivers) to energy consumption. They divided these drivers into five groups: physical environmental factors (ex: temperature and humidity), contextual factors (ex: building orientation), psychological factors (ex: indoor temperature setting), physiological factors (ex: age and gender) and finally social factors (interaction between household members). As a result, Fabi et al. (2012) conclude that energy consumption determinants in residential buildings are related

either to the climate, the building characteristics, or to the occupants and their behavior. Physical factors, such as climate, the size, age, and construction type of each dwelling, the number and age of its occupants, and the amount and types of electrical appliances, are fairly straightforward (Lutzenhiser and Bender, 2008; Mansouri et al., 1996; McLoughlin et al., 2012; Santamouris et al., 2007; Yun and Steemers, 2011a). A study conducted by Lutzenhiser et al. (2008) includes income, education, family size, number of occupants, occupation hours, size and type of dwelling, and household type (e.g. young singles, young families, families with teenagers, and retired households) as influential on energy consumption. Guerin et al. (2000) identify household income, age, education of owners, home ownership, desire for comfort, and energy conservation incentives as influencing factors. McLoughlin et al. (2012) conduct a literature review to identify the key variables that influence electricity consumption at home. They rank these variables according to their number of citations in the literature review. Among the most important variables related to dwellings, McLoughlin et al. (2012) identify dwelling type, location, age and surface area. As for occupant-related variables, they distinguish the number of occupants, disposable income, head-of-household age, tenure type, social group, education level, and appliance ownership. Other variables concerning climate and temporal context are, for example, external/internal temperature and the day (weekday/weekend).

A number of studies confirm the relevance of correlations between the determinant variables of energy consumption. Morely et al. (2011) conclude that when studying statistical energy consumption data, the results of regression analyses could not be interpreted easily. Morely et al. (2011) explain the reason by the high interrelations between energy consumption determinants. Authors such that Santamouris et al. (2007) assert that household income is an important determinant of the size, age, type of dwelling and type of equipment. Yun et al. (2011a) find that the most significant factors associated with the ownership of air conditioning systems are climate and household annual income. McLoughlin et al. (2012) confirm that dwelling age and tenure type are highly correlated with head-of-household age. The same authors reveal that head-of-household employment status and education level reveal high correlation to head-of-household's social class. Nugroho et al. (2010) study the cause-effect relationships between energy consumption and its determinants. They conclude that household's age and education level have significant influence on the ownership of home appliances. As a result of these findings, one can

conclude that complex interrelations exist between variables related to households, dwellings and environment and that they greatly influence energy consumption trends of buildings.

2.2.4 Occupants and energy consumption in residential buildings

The energy use of buildings is strongly dependent on the general behavior of occupants. According to Ellegård and Palm (2011), energy use is embedded in most aspects of households' daily life. People use energy to satisfy certain daily living activities such as preserving and preparing food, supplying heat and light, and maintaining health and sanitation (Kashif et al., 2011; Pennavaire, 2010). Authors such as Page et al. (2008) and Robinson (2006) explain that the influence of occupants on the buildings' energy performance can be translated by their presence (internal heat gains, emission of pollutants such as Co₂, water vapor, odors, etc.) and the actions they perform (activities such as cooking, using light, etc.), as well as their interactions with the controls of inherent building systems designed for adjusting indoor environment variables (ex: changing thermostat setting-temperature for thermal comfort, adjust lighting intensity for visual comfort, etc.). According to Robinson (2006), the most complex processes taking place within buildings are those that result from human behavior. These interactions have important implications for a building's energy balance, affecting both the indoor microclimate and the demands for applied energy. The author concludes that the presence of the occupants in a building and the activities they undertake within it are stochastic and not easy to predict. Robinson (2006) identified the following human interactions which influence the energy balance:

- Window and door openings: influencing air flow,
- Shading devices / blinds: influencing radiation transmission and glass surface temperature,
- Lighting controls: influencing electricity consumption and casual heat gains,
- Electrical appliances: influencing electricity consumption and casual heat gain,
- Heating, ventilating and cooling system controls: influencing thermal and electrical energy consumption and associated heat injection / rejection, and finally
- Waste is also produced, from which energy may be derived, and water is consumed.

MacDonald et al. (1999) emphasize also that occupants have a major influence on the energy performance of buildings as they control the internal temperature, ventilation, lighting, equipment, and hot water.

Energy consumption can vary dramatically between different households. This variation is due to the variability in occupant profiles (socio-demographic and economic attributes) which leads to variability in equipment possession and energy consumption patterns. According to Swan and Ugursal (2009), occupant behavior in the residential sector varies widely and can impact energy consumption by as much as 100% for a given dwelling. Clevenger & Haymaker (2006) confirm the role of occupant behavior as a substantial source of uncertainty in energy modeling. These authors discovered that a variation in occupants' presence in a school building may yield a variation of more than 150% in energy estimations. Seryak and Kissock (2003) analyzed energy use characteristics of university residential homes in relation to number of occupants, time of occupancy, weather, house, structure quality, and occupant behavior. They found that a same house occupied during two years by different occupants can have different energy consumptions due to the different behavioral patterns of these occupants. Emery and Kippenhan (2006) investigated the effects of occupants' presence on building energy consumption for four nearly identical houses and found that the presence of occupants can increase the total energy consumption. Masoso & Grobler (2010) conducted an energy audit on six randomly chosen commercial buildings in Botswana and south Africa. They measured the energy consumption during a period of one month, where energy consumption was broken down into heating, ventilation and air conditioning (HVAC), plug load (office equipment) and lighting. The results show that more than 50% of energy is used during non-working hours. The major energy consumers were found to be air conditioning systems, followed by equipment that are left ON unnecessarily at the end of day (mostly computers), and finally lighting. The authors confirm the responsibility of poor occupant behaviors on this waste of energy.

In the scope of improving energy efficiency in residential building in US, Yun & Steemers (2011b) investigated the significance of behavioral, physical and socio-economic parameters on the energy consumption of cooling devices. The authors carried out a detailed analysis of a large database of real measured domestic energy use. They demonstrated that behavioral and socio-economic factors exert a significant indirect as well as direct influence on energy use, showing

that it is particularly important to understand indirect relationships. Pachauri (2004) conducted an econometric analysis using Indian household survey data. Using these data, Pachauri developed an empirical (regression) model to formalize and quantify the knowledge and understanding of the relationships between household energy requirements and economic variables. The author found that variables that have an impact on total household energy requirements can be grouped in three different categories: economic variables (total household expenditure), demographic variables (rural/urban location, number of household members) and dwelling attributes (covered area of dwelling, construction type, dwelling type). The study revealed that household socio-economic, demographic, geographic, family and dwelling attributes has a substantial influence on total household energy requirements, and that income level is the most important explanatory variable causing variation in energy requirements across different households.

Other researchers such as Raaij and Verhallen (1983) and Paauw (2009) developed sets of energy-use profiles according to occupants attributes and energy consumption drivers. Based on four variables (home temperature during presence and during absence, airing rooms, and use of the hall door), Raaij and Verhallen (1983) grouped energy use patterns of heating systems into five major behavioral clusters: conservers, spenders, warm, cold and average profiles. Similarly, Paauw (2009) distinguishes four different energy user profiles: the 'Convenience/Ease' profile: people in this profile act because of comfort needs and have no interest in energy use, money, nor environment; the 'Conscious' profile: these people choose for comfort, but are very aware of the consequences for the environment and their own financial situation; the 'Costs' profile: people are very aware of the (energy) costs and consume as little energy as possible to save money; and finally the 'Climate/Environment' profile: these people act entirely because they care about the environment.

Similarly to these clustering approaches, a study by the sociologists from the French scientific and technical centre for building (CSTB) examines the influence of practices, rationalities and motivations of French occupants on the residential energy consumption (Roudil et al., 2012). The authors identify three structural drivers of residential energy consumption which are economic resources, social norms, and material and technical culture of occupants. Roudil (2012) uses these drivers to cluster the French population into four different profiles each having its own energy

consumption practices. By this clustering, the authors confirm the direct influence of occupant's socio-demographic and economic profile on households' energy consumption patterns.

As a result of these findings, one can deduce the direct influence of occupants on buildings' energy performance. They are not only a substantial source of consumption, but also a major reason behind variability in this consumption since behavioral patterns can vary considerably from one household to another (Chiou, 2009a). Households with different socio-demographic and economic attributes have different energy consumption profiles. Due to this complex and diverse nature of users' energy consumption behavior, general assumptions about this consumption have thus high ambiguities and inevitably lead to significant uncertainties in energy predictions (Clevenger and Haymaker, 2006). For these reasons, current energy simulation tools used in the industry seem to be incapable of giving exact predictions of these consumptions since they can only imitate behavior patterns in a rigid way. This last point is further discussed in the following section related to modeling occupant-related energy consumption in buildings.

2.3 The human behavior: a complex phenomenon

As concluded from the preceding section, the behaviors of occupants in residential buildings are considered as complex phenomena and are not easily understood. In order to have a clear image about how occupants perceive, reason and carry out their behavior in general, and in buildings in particular, a part of our literature review was dedicated for this issue. In this section, we expose a brief presentation for some of the theories whose objective is to assess human behavior and its complex structure.

These theories stem from disciplines such as sociology, psychology, ergonomics and anthropology. Theories such as the theory of reasoned action, the theory of planned behavior and the activity theory are well known in this domain. The theory of planned behavior (TPB) describes the factors that determine an individual's decision to follow a particular course of behavior. This theory is itself an extension of the widely applied theory of reasoned action (Ajzen, 1991). TPB proposes that the proximal determinants of behavior are intention to engage in that behavior and perceptions of control over that behavior. Intentions represent a person's motivation in the sense of his/her conscious plan or decision to exert effort to perform the behavior. Perceived behavioral control is a person's expectancy that performance of the behavior

is within his/her control. Control is seen as a continuum with easily executed behaviors at one end and behavioral goals demanding resources, opportunities, and specialized skills at the other. Intention is itself determined by three sets of factors: attitudes, which are the overall evaluations of the behavior by the individual; subjective norms, which consist of a person's beliefs about whether significant others think he/she should engage in the behavior; and perceived behavioral control, which is the individual's perception of the extent to which performance of the behavior is easy or difficult (Figure 2.4).

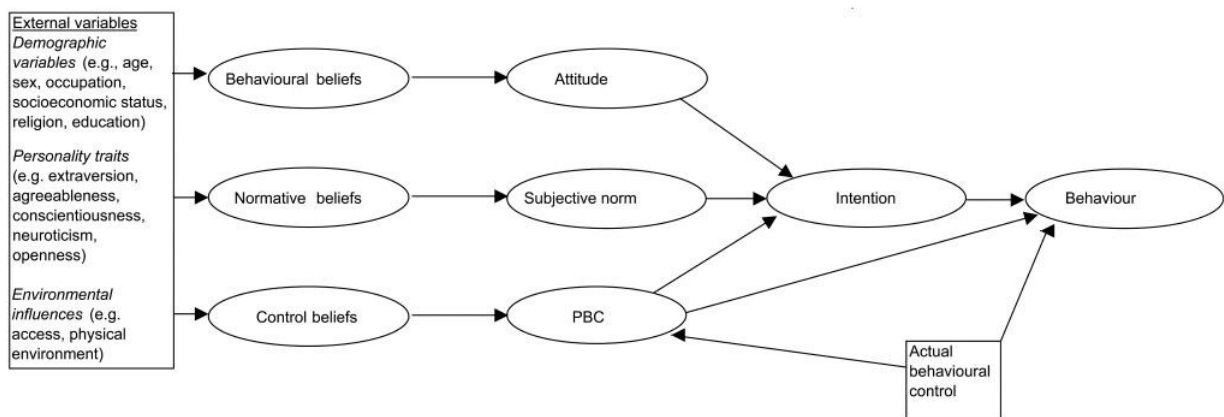


Figure 2.4 : Theory of planned behavior (TPB) (Excerpt from Conner & Norman (2005))

Activity theory is another paradigm describing human behavior from a socio-cultural perspective (Kaptelinin, 2012). The foundational concept of the framework is “activity”, which is understood as purposeful, transformative, and developing interaction between actors (subjects) and the world (objects). Psychologists such as Leontiev (1981) and Rubinshtein (1989) define human behavior using a three-layer model comprising activities, actions and operations (Figure 2.5). Complex relationships between motives (i.e., what motivates the activity) and goals (i.e., what directs the activity) are a characteristic feature of humans.

Given that energy consumption within buildings is the result of certain human behaviors, the above theories present thus potentials to assess human behavior and the complex phenomena influencing it. They can help in exploring and understanding such behaviors.

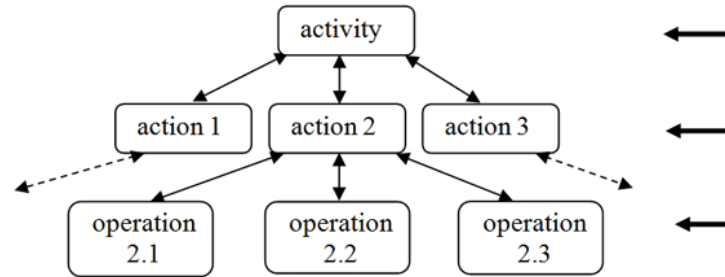


Figure 2.5 : Hierarchical structure of human activity according to the Activity theory of Leontiev (From Kaptelinin (2012))

2.4 Modeling and simulating energy consumption in residential buildings

Energy consumption modeling of buildings seeks to quantify energy requirements as a function of input parameters. According to Swan and Ugursal (2009), models may be used for a variety of reasons, the most common being the determination of national or regional energy supply requirements (macro-scale) and the change in energy consumption of a particular dwelling due to an upgrade or addition of technology (micro-scale). Energy models are used for forecasting energy consumption of future buildings, for developing new technologies, for predicting energy savings, and even for promoting energy conservation programs and incentives. The choices regarding modeling techniques and model variables are made as a function of data availability and model objectives.

In this section, we first give a brief presentation of energy modeling tools used in buildings' industry nowadays. Later on, we expose a structured literature review about the general approaches and techniques that were developed for modeling energy consumption in buildings.

2.4.1 Theoretical frameworks of residential energy use

In the scope of describing the relation between occupants' behaviors and residential energy consumption, a number of theoretical frameworks were developed. These frameworks combine social and technical perspectives of energy consumption related to occupant behavior, typically, with a starting point in the social perspective comprising sociology, anthropology, and psychology (Larsen et al., 2010). Raaij and Verhallen (1983) proposed a comprehensive model of

residential energy use that relates personal, environmental, and behavioral factors. The authors divided the factors influencing the energy consumption into three types: purchase related, usage related, and maintenance related where all of them are related to each other. Hitchcock (1993) developed an integrated framework for energy use and behavior in the domestic sector. The author explain that energy consumption patterns are a complex technical and social phenomenon that must be viewed from both engineering and social perspectives in order to be fully understood (Figure 2.6).

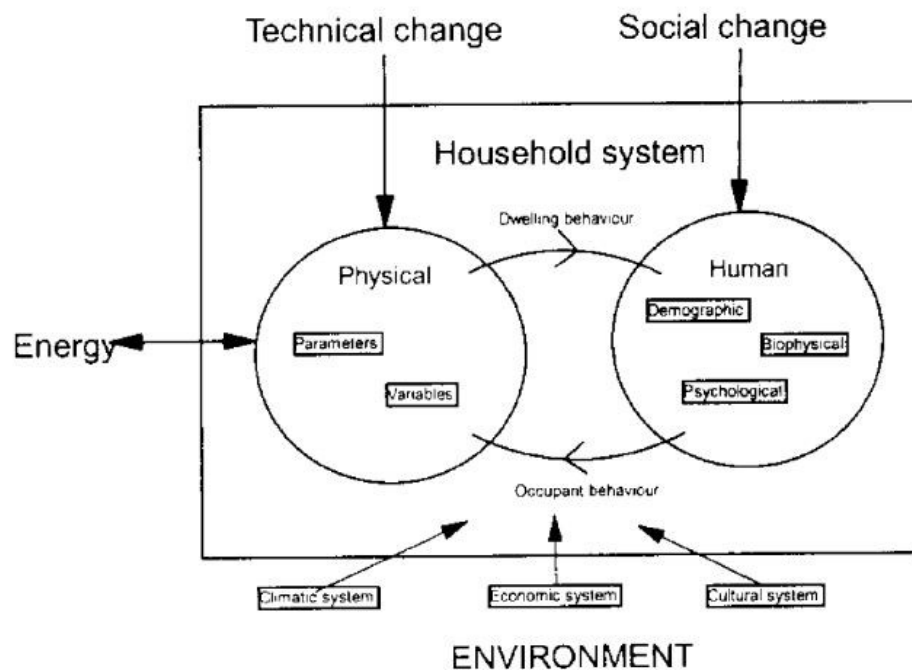


Figure 2.6 : Integrated framework of energy use considering engineering and social perspectives (Excerpt from Hitchcock (1993))

The framework of Hitchcock suggests the main components of the technical and social perspectives, respectively, as well as the important interaction between the perspectives. The author concludes that for most other models, “occupant behavior” expresses the two-way interaction between the physical and human spheres, whereas his model defines “occupant behavior” as the one-way link from the human system to the physical system and the so-called “dwelling behavior” as the opposite one-way link from the physical system to the human system. The social perspective of the framework comprises the human system together with the two environmental factors: economic system and cultural system. The engineering perspective

comprises the physical system together with the climate system as an environmental factor. Weber & Perrels (2000) developed an approach to analyze and quantify the impact of lifestyle factors on current and future energy demand. Their approach provides a comprehensive methodology to analyze environmental effects in a consumer and citizen perspective and thus contributes to an increased transparency of complex economic and ecological interconnections. The model proposed comprises societal hyper structure, manifest lifestyle, energy use, and environmental impacts.

Such integrated models are till now considered as very important due to their systematic way of depicting residential energy consumption. Despite the value of such cross-disciplinary models, it appears they are little used, and in practice single-discipline studies dominate the literature. Keirstead (2006) concludes that such models have “failed to spark a significant debate within the literature as to how such an integrated approach might be structured or implemented”.

2.4.2 Energy simulation tools: adopted models

During the design phase, designers and experts rely on simulation tools for assessing and predicting buildings' future energy performance. Several energy simulation tools such as EnergyPlus, eQUEST, ESP-r and TRNSYS are available today in the market (for more detailed reading about available building simulation tools, refer to Crawley et al. (2005) and Fischer & Kunz (2004)). Energy simulation tools predict the energy performance of a given building and thermal comfort for its occupants. In general, they support the understanding of how a given building operates according to certain criteria and enable comparisons of different design alternatives. In general, simulation tools take a number of different parameters as inputs such as building geometry and weather conditions (Figure 2.7). Every energy simulation engine is based on thermodynamic equations, principles and assumptions. According to Fischer & Kunz (2004), input data, especially weather data and internal loads, are based generally on assumptions. Hence, the prediction of absolute energy values of an energy simulation, given these assumptions, is rarely accurate. Malavazos et al. (2011) confirm that variations are present between real consumption values and predicted consumption through simulation tools. They emphasize that such tools focus primarily on the structural behavior of buildings and their relations to specific environmental conditions while taking insufficiently into account the role of the occupants

(Malavazos et al., 2011). This last point is the main limitation of existing energy simulation tools nowadays.

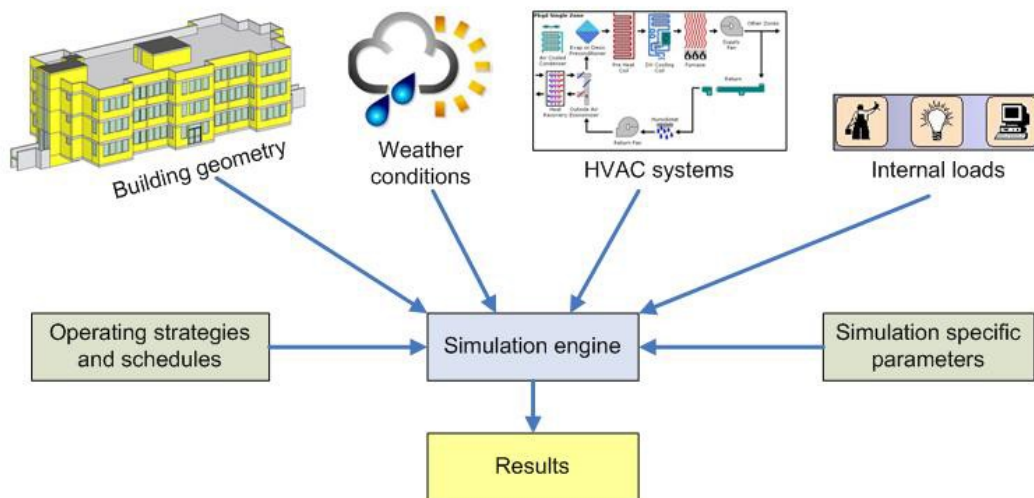


Figure 2.7 : General data flow of energy simulation engines (Fischer and Kunz, 2004)

Due to the complexity with capturing user preferences and energy consumption patterns, existing simulation tools tend to eliminate the influence of occupants behavior as far as possible to optimize building performance eventually leading to unrealistic assumptions about average user preferences and behaviors (Kashif et al., 2012; Malavazos et al., 2011). For example, the most common way in which these simulation tools consider occupant presence and interaction with buildings is through so-called diversity-profiles. These profiles are defined in the form of time schedules that indicates the presence or absence of occupants at home (Abushakra et al., 2000). Diversity-profiles are mainly used for estimating internal heat gains from people, household appliances and lighting. The profiles depend on the type of building being analyzed, typically distinguishing between residential and commercial buildings. Diversity profiles however fail to sufficiently capture dependencies of occupancy patterns with energy consumption (Bourgeois et al., 2004; Page et al., 2007). According to Chiou (2009a), this is an obvious shortcoming of the “one-size-fits-all” diversity profiles. Another example of these simplifications is that simulation tools do not account for domestic appliances which are installed and used by buildings’ occupants. These appliances can constitute a major part of households’ energy consumption, electricity in particular, are also a main reason for consumption variability between different families living in two similar dwellings for instance.

In France, diversity profiles are also adopted in energy simulation engines, for example in the latest the building regulation in France (RT2012). For instance, the lighting use scenarios defined in RT2012 consider that occupants use artificial lighting only in the case where natural light is unavailable. The calculation method integrated in the engine of the mentioned norm assumes that the power of artificial lighting installed in a building is equal to 1.4 Watts per square meter, and that only 10% of lighting points will be turned on simultaneously, which is likely to be far from the reality.

Researchers highlight that the importance of energy simulation tools lies in their ability to evaluate alternatives rather than accurately predict energy performance. However, to fully contribute to the design process, these tools must become more reliable and accurate in predicting actual building performance (C. Clevenger and Haymaker, 2006). Larsen et al. (2010) emphasize however the need for developing more precise methods for modeling occupants influence on whole building performance. Authors such as Fischer and Kunz (2004) propose that statistically derived stochastic distributions may provide a methodology to simulate the actual behavior of people in buildings more accurately. However, the authors conclude that none of the energy simulation tools provide such functionality.

2.4.3 Modeling energy consumption in residential buildings: Existing approaches and techniques

In literature, a number of techniques and approaches have been developed to address the issue of modeling energy consumption in residential buildings. According to Swan and Ugursal (2009), the two major streams of approaches identified are top-down and bottom-up approaches, with each of them comprising a number of scientific techniques. Top-down approaches use high level data such as national energy statistics to derive causal relationships between electricity consumption and its determinants. On the other side, bottom-up models use data collected at an individual dwelling level to determine relationships between household characteristics and electricity use. The most frequently used techniques for bottom-up approaches are statistical regression and engineering techniques (McLoughlin et al., 2012; Swan and Ugursal, 2009). The deployment of Statistical/regression models is feasible when large sub-metering datasets are available. These models provide a good understanding of electricity consumption patterns as they

are based on real data. Their main drawbacks are their implementation cost and sometimes the occurrence of multi-collinearity between variables. Engineering models are “bottom-up” approaches that necessitate information concerning appliance power ratings or end-use characteristics to build up a description of electricity consumption patterns. The major strength of such models is that they are the only methodology that can model electricity consumption without any historical information on electricity use. The difficulty associated to engineering models is the complexity of their implementation and validation.

Models found in the literature differ from each other depending on the objectives aimed by the authors. For example, some models are established to estimate energy demand (Chiou, 2009b; Muratori, 2012; Richardson et al., 2009; Stokes et al., 2004; Widén et al., 2009) , others for identifying possible energy savings (Krarti et al., 2005; Richardson et al., 2009), monitoring energy consumptions (Firth et al., 2008), or even developing methodologies to evaluate energy efficiency programs and promotion campaigns (Martinot and Borg, 1998; Vine and Fielding, 2006). The majority of these models include aspects of mass and energy conservation in shape of different tools and techniques to determine the energy consumption.

2.4.4 Occupant-related energy consumption models

According to literature review, the research on occupant-related residential energy consumption can be divided into two groups of methods. The first group consists of using real sub-metering data in order to derive representational load or diversity profiles of occupants energy use. Using these load profiles, estimates of buildings’ energy consumption can be deduced. The second group of studies focuses on the development of approaches that can better represent occupants’ behavior. Such models aim at simulating occupancy patterns and various energy-load schedules by using stochastic approaches. Authors such as Seryak & Kissock (2003), Yohanis et al. (2008) adopted the first group method, that is the use of sub-metering data. Although such models can generate representative load profiles and provide some insights about occupants’ role in energy consumption, yet they do not depict the complex phenomena of occupant behavior. Instead of using sub-metering data, the studies from the second group use other source of information, namely the time use surveys (TUS). The latter can be defined as large-scale time-use surveys administrated conducted at the national level. Each TUS record contains information on 24-hour

period of activities of a given individual (Chiou, 2009b). A number of authors have used such surveys so that to depict and model occupants' daily energy use. Among all daily living activities of the TUS, they consider only the energy-consuming ones. Then by applying stochastic techniques such as Monte Carlo Markov chains (MCMC), they can derive daily activity patterns of energy consumption.

Shimoda (2004) and Yamaguchi et al. (2003) were among the first authors who based their energy models on time use surveys. Shimoda (2004) used data from 2000 Japanese Time-Use Survey (JTUS) to create typical occupant schedules for residential end-use energy simulations of Osaka City. Tanimoto (2008) proposed a stochastic approach for residential cooling-load calculations. The same author develops later a method to simulate the load schedules for appliances, lighting, and hot water (Jun Tanimoto et al., 2008). Tanimoto (2008) does not offer any discussion regarding the strength and limitation of his approach. Richardson et al. (2008) introduce a Markov-chain technique to generate synthetic active occupancy patterns, based upon time-use surveys in the United Kingdom. In this approach, the activities of the TUS data are reduced to 3 states: not-in-residence, in-residence and active, and in-residence and not-active (e.g., asleep). The stochastic model proposed by Richardson et al. provides a mapping between occupant activity (state) and appliance use, creating thus highly resolved synthetic energy demand data. In their results, Richardson et al. (2008) find good match between occupancy profiles yielded by the model and real profiles taken from the TUS data. Based on their occupancy model, the same authors also develop a lighting model in (Richardson et al., 2009) and later on an a domestic electricity demand model (Richardson et al., 2010).

Widén and Wäckelgård (2010) develop a high-resolution stochastic model of domestic activity patterns and electricity demand in Sweden. They identify nine different electricity-dependent activities such as sleeping, cooking, dishwashing, cloth washing, TV and others. The authors associate then each of these activities to its corresponding domestic appliance(s). By defining load patterns for each appliance, Widén and Wäckelgård estimate the total electricity demand per household. The model is calibrated and validated against relatively small time-use and electricity consumption datasets collected in Sweden. The authors show that realistic demand patterns can be generated from these activity sequences. Muratori (2012) use heterogeneous Markov chains to model domestic activity patterns of individuals and thus to predict energy consumption of

households. Subbiah (2013) uses American TUS data for developing a disaggregated energy demand-modeling framework that estimates energy demand profiles based on individual-level and building-level energy-consuming activities. The modeling framework generates energy demand profile at a regular basis by taking into account the physical, behavioral, economical and social factors affecting the energy consumption. The residential energy demand model associates appliance usage for each household activity and calculates energy consumption based on the appliance energy rating and duration of activity. Subbiah (2013) claims that his model can result in better results than other TUS-based models since it can account for interactions between household members and that it computes domestic activities at both individual and household levels.

A system dynamics approach was adopted by Sorasalmi (2012) for modeling the evolution of long-term domestic electricity demand. The objective of the model is to generate energy load profiles. In addition, the approach can model future changes in electricity consumption due to variables such as growth in population, dwelling stock, appliance stock and increase in energy efficiency. According to Sorasalmi (2012), the preliminary results of the proposed model suggest that the approach is useful and it can be used to better understand how load profiles are composed and how decision makers can influence them.

In the very recent years, approaches stemming from the artificial intelligence domain have started to be applied for modeling energy consumption in buildings. According to Liao et al. (2012), constructing mathematical models of occupancy dynamics in a building is a challenging problem because of the high uncertainty of people movement. On the high-resolution end of the spectrum of modeling possibilities lie the so-called agent-based models. An agent-based model consists of agents (encoded in software) in which each agent is endowed with a set of behaviors that are designed to imitate humans' behavior under situations that the model is meant to study (Liao et al., 2012).

Kashif et al. (2012) proposed a conceptual framework to simulate dynamic group behavior by using an agent-based approach. The proposed framework is used as a simulation environment for energy smart homes that takes into account inhabitants' dynamic and social behavior. The authors used this environment to predict the energy consumption of a household by simulating

the interactions between inhabitants living in the same home, as well as their activities. Quijano et al. (2010) proposed an agent-based simulation platform called SMACH (multi-agent simulation of human behavior) for assessing the impact of the adaptive behavior of various electrical appliances on the overall consumption of dwellings. To do this, the platform SMACH models the behavior of electrical appliances as well as those of individuals. Two types of agents are identified: devices agents (having intelligent behavior) and the human agents. The human agents imitating individuals' behaviors are modeled from observations in the real world of some volunteer families. The behavior of a device itself is represented by its current state and its impact on the comfort of the inhabitants. As concluded by Quijano et al. (2010), the major limitation of their work is that the different strategies have not been tested in a real environment and that it would be difficult to identify the activity of each individual at every moment. This conclusion is important to show the shortcomings of such dynamic modeling approaches. Moreover, high computational and time costs are also two major shortcomings of such dynamic approaches.

2.5 Research gaps in occupant-related energy consumption models

As we mentioned earlier, choosing an approach for developing an energy consumption model is directly related to the research context and the objectives envisioned by this model. Therefore, in this section we identify a number of research gaps a function of the research questions that we identified earlier.

First of all, we emphasize that the main objective envisioned by this research work is to develop a model for forecasting spectrums of energy consumption corresponding to occupant-related activities in residential buildings. We do not aim at modeling the dynamic nature of energy consumption, but we rather search at quantifying this consumption as a function of households' attributes. The major aims intended through this model are:

- First to provide realistic and accurate predictions of residential energy consumption at a very fine granularity (at the level of domestic activities).
- Second to provide energy estimates disaggregated to the level of households and individuals as a function of their socio-demographic and economic attributes.
- Third to be able to assess the variability in energy consumption between different individuals and households with different attributes (different profiles).

Given these research perspectives, we identify the following shortcomings associated to models found in literature review:

- First: Even though most of the models highlight a relatively high number of energy consumption determinants related to occupants (such as the income, age, etc.), yet they are still too far simplistic with representing these determinants. In most of these models, the main variable considered for representing households' attributes is the number of occupants. This means that such models cannot assess variability of energy consumption for instance between two households having the same number of occupants but of different socio-economical attributes.

- Second: There has been little published work for generating energy demand profiles with a very fine granularity. The models in literature do not provide the complete ability to quantify energy consumption at the level of a specific household or a specific individual according to their social, demographic, and economical characteristics.
- Third: Most of the published models are based either on monitored consumption data or on time use surveys. The reliability of these data sources can be criticized since it represents only a part of the population, and not the whole population. For instance, time use surveys only consider activity schedules of the individuals who responded to the survey; thus, other household members are considered as having same activity schedules which is not rational and can lead to unrealistic energy demand predictions.
- Fourth: These models do not present a clear view on how domestic activities can be carried out by and shared among household members. The aggregation of individual activity quantities at the level of the household has not been tackled. For instance, if two or more individuals are watching TV at the same time, the energy consumption of the TV appliance must be counted only once.

The literature review conducted in this second chapter, and the above analysis of research gaps, were used as a basis for constructing our research approach. The latter is to be presented in the next chapter in details, where each of the abovementioned points will be exposed.

Chapter 3: Stochastic activity-based approach for modeling occupant-related residential energy consumption

In this chapter, we first propose a systemic view of energy consumption in residential buildings based on the literature review. Second, a systematic breakdown structure of energy end uses at the different levels of the building is established. Third, we propose a stochastic activity-based approach for modeling occupant-related energy consumption (SABEC). Model's structure, its variables, and the statistical data used are presented.

3.1 Systemic view of residential energy consumption

As we have seen in the previous chapter, energy consumption in residential buildings is considered as ambiguous due to the large number of determinants influencing it. The literature review classifies these determinants into three main groups which are: building's physical characteristics and inherent systems, external environment, and occupants. In this section, we propose a systemic view of residential energy consumption according to these three groups, and based on a framework developed earlier by Soldaat (2006). From a systemic point of view, three main systems that govern energy consumption in residential building can be identified: the household system, the artifact system, and the environment system. These are represented through Figure 3.1 while their taxonomy is given hereafter.

- **Artifact system:** represents the set of artifacts (objects made by humans) present in the whole system. These are mainly the dwelling itself and the equipments present inside. A dwelling is the place where individuals live and perform their daily living activities. It provides different functionalities for its occupants, and is characterized by its physical attributes (surface area, age, etc.) and the technical equipments (heating, cooling, lighting, ventilation, and auxiliaries). The personal equipments are the devices or appliances owned by occupants and not inherent to the building. Examples of these equipments are washing machine, dishwasher and lighting equipments. The ownership and the characteristics of these equipments change among households as a function of household's attributes. The equipments are used by households to perform their daily activities and they consume energy and water.

- **Environment system:** represents the elements present outside the dwelling, but can have direct influence on the energy-related usage of the occupants. These include physical-environment parameters (e.g. temperature and luminosity) and temporal context parameters (e.g. season).

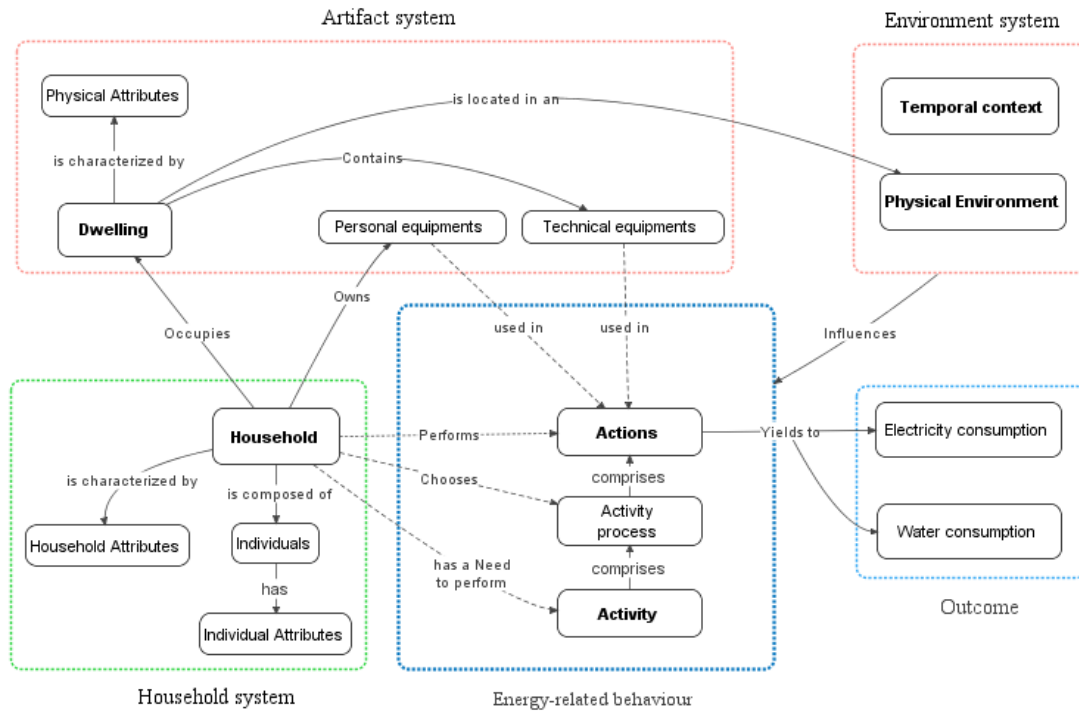


Figure 3.1: Systemic view of energy consumption in residential buildings

- **Household system:** The household system consists of one or more individuals living in a dwelling. Individuals of a household interact with each other and with the artifact & environment systems. Household individuals perform activities to satisfy their daily living needs. When carrying out activities, they use equipments, and thus consume energy. Households and individuals are characterized by a number of variables representing their demographic, socio-economic, and behavioral attributes.
- **Energy-related behavior:**

Households perform domestic activities to satisfy their needs and well-being, such as house caring activities (washing dishes, vacuuming), self care activities (bathing), and entertainment activities (watching TV). Most of these activities require the usage of certain equipments that

consume energy (electricity and water). The way how a household performs activities is influenced directly by the habits and lifestyle of its individuals as well as their personal preferences (for example: use of appliances, lighting levels, indoor temperature preferences, etc.). In this perspective, household's variables such as the size, composition, life stage, and income must be taken into account.

According to Activity Theory (chapter 2), the energy-related behavior of building occupants may be represented by their daily activities. We define here activity as the following:

- **Activity:** An activity is a functional element performed by an individual or group of individuals in order to satisfy their daily living needs and well-being.
- **Process:** Each activity has one or more ways to be carried out, namely activity-process. The process describes how an activity is performed. The choice of a process depends directly on the individuals and household characteristics. For example, “washing dishes” activity may have two processes: washing by hands or washing by machine.
- **Action:** The activity-process is carried out through elementary actions. The actions are the elements of the activity which relate directly to energy-consumption. Appliances may be used through actions. For example, the temperature setting and the filling ratio of a washing machine are two actions of the “washing laundry” activity.
- **Outcome:** Is the result of the interactions between household system and building and environment systems. It is thus the direct result of the energy-related behavior. When household individuals perform activities and use equipments, they consume energy and water.

The systemic representation presented in this section is essential for depicting energy consumption at the different levels of the building, whilst identifying the influencing factors related to occupants and their context. This allows a more comprehensive modeling of residential energy consumption. It is also essential in understanding the reasons behind the variability of energy consumption between a building and another, and between a household and another.

3.1.1 Breakdown structure of energy consumption in residential buildings

As highlighted in chapter 2, the energy use of domestic buildings can be divided into two categories of sources. The first category encompasses the energy used by indoor environmental-control devices and systems such as lighting, heating, ventilation and air conditioning (HVAC) that occupants use for adjusting their wellbeing comfort level. The second category however includes the appliances that occupants use for performing their daily living activities such as cooking, washing, and entertainment. In order to better represent these energy uses, we propose here a breakdown structure which segregates residential energy consumption at three levels. The proposed breakdown structure is illustrated in Figure 3.2

The first level is the building level, which comprises the end-uses of inherent systems and equipments installed for the general services of the building. These end-uses are: heating, cooling, ventilation, lighting (in building's common areas), and domestic hot water. The influencing factors of energy consumption at this level are mainly attributed to building's physical characteristics (orientation, insulation, wall type, etc.) and to the external climate.

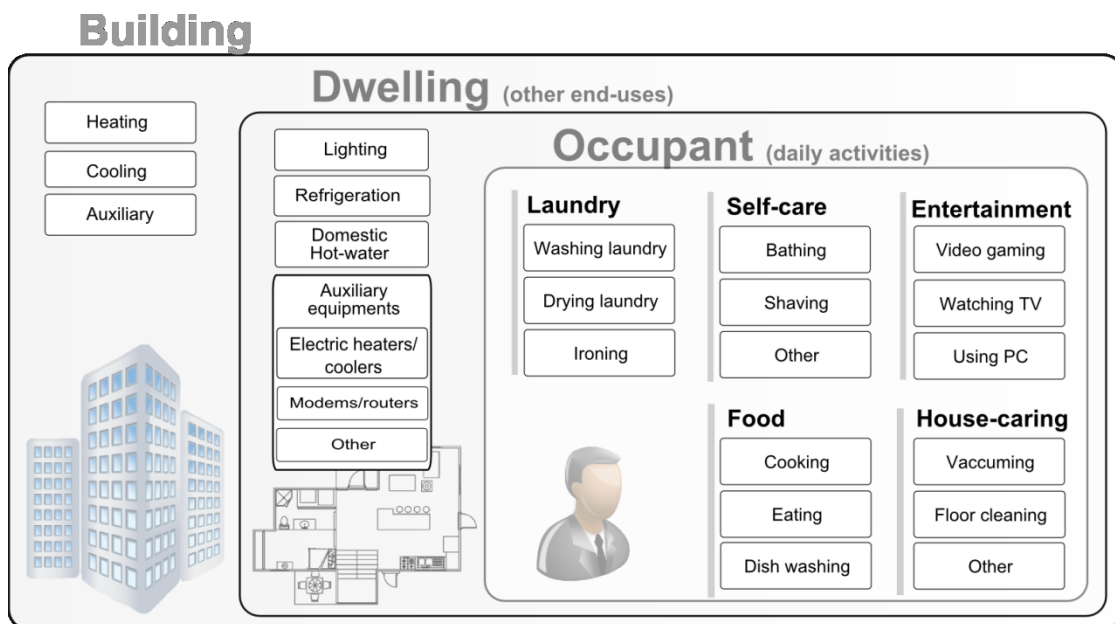


Figure 3.2: Systematic breakdown structure of energy consumption in residential building

The second and third levels represent the energy consumption due to occupants' activities and their domestic appliances. More precisely, the second level corresponds to energy consumption at

the level of the dwelling. The energy consumption at this level comprises the common energy usages of occupants at home which are: lighting (inside the dwelling), cold (refrigerators and freezers), personal heating and cooling (that use electricity), and other auxiliary equipments (such as internet boxes, routers, etc.). The consumption pattern of these end uses is said to be transversal or diffuse. Some of them consume energy continuously (such as refrigerators) and others non-continuously (such as lights). Their use by household members is not seen as a major objective itself, but it is rather for accompanying other domestic activities (e.g. using light for reading or for eating).

At the third level of energy consumption, we position the activity-related energy consumptions which are mainly influenced by occupants' attributes and lifestyle. At this level, energy is consumed due to intentional domestic living activities such as watching TV, washing dishes, doing laundry, etc. The different activities can be grouped in what we call aggregated activities which are defined according to the daily life needs of household members. For instance, under the aggregated activity "Laundry", we can find the three elementary domestic activities: washing clothes, drying cloths, and ironing. More details about these activities is given in the next section.

The energy consumption of end-uses such as heating, cooling, lighting, ventilation and domestic hot water depends highly on the structural characteristics of the building. As seen in chapter 2, a good understanding of these end-uses has been established, and international regulations and documentations are settled. Their yielding energy consumption is thus modeled and simulated within energy simulation tools with a good precision.

On the other side, energy consumption of domestic activities such as cooking, multimedia, informatics and others is still less explored. In fact, energy consumption at the third level (occupant level) represents the major part of the specific electricity use which we evoked in chapter 2. For the case of green buildings, these end uses are highly contributing to the total energy consumption of the building. In addition to their high consumption levels of energy and water, a main feature of these end uses is their variability among different households due to their high dependency on occupant's socio-economic and demographic characteristics (Ellegård and Palm, 2011).

3.1.2 Activity-based modeling of residential energy consumption

It is only recently that the “activity” notion started to be introduced within energy consumption models. A number of studies have identified major domestic activities that consume energy at home, and developed what is called activity-based models. Authors such as Pennavaire (2010) and Kashif et al. (2011) highlight that people use energy to satisfy certain daily living activities such as preserving and preparing food, supplying heat and light, and maintaining health and sanitation. Ellegard et al. (2011) identify seven main categories of the household’s everyday activities such as care for oneself, care for others, household care and others. Their study reveals that the pattern of these activities differs from one household to another depending on peoples’ characteristics. Widen et al. (2010) develop a high-resolution stochastic model of domestic activity patterns and electricity demand in Sweden. They identify nine different electricity-dependent activities such as sleeping, cooking, dishwashing, cloth washing, TV and others. The authors associate then each of these activities to its corresponding domestic appliance(s). By defining load patterns for each appliance, Widen et al. can estimate the total electricity demand of households. Muratori et al. (2012) adopt the same classification of domestic activities as Widen et al.. Chiou et al. (2009b) use the results of a detailed American time-use survey (ATUS) to identify a list of different daily living activities. Morley and Hazas (2011) identify what they call practices of daily living, such as watching TV, entertainment, main meals, baking, ironing, using coffee machine, and going away at weekends. Richardson et al. (2010) use a similar approach by defining six activities and associating them to domestic appliances. Other authors such as Tanimoto et al. also use an activity-based approach to estimate energy consumption of occupants in residential buildings (Jun Tanimoto et al., 2008).

The above presented models give a description of residential energy demand based on domestic activities. All of these models are based either on times use surveys (TUS) or measured consumption data to construct relations between households, their daily activities, and domestic appliances. Yet, their main drawback is that no real comprehensive activity-based model of energy consumption is developed. By this we mean that energy-consuming activities are not represented through an overall view which describes their nature and interrelations. In addition, the variables characterizing each activity and the way these variables relate to household characteristics are not dealt with. Another important shortcoming is that they do not present an

approach for quantifying activities and their yielded consumption as a function of individuals' and households' socio-demographic attributes.

3.1.3 Relations between household attributes and domestic activities and appliances

Literature study confirms the presence of high correlations between household attributes from one side and domestic appliances ownership levels, use patterns, their type and energy rating from the other side. In this section, we present a brief description of such relations.

3.1.3.1 Appliances ownership

A Belgian study assesses household electric appliances, their ownership rate and use trends as a function of different consumer profiles (Crioc, 2009). According to this study, some devices are present in the majority of households, such as refrigerator, television, washing machine, while others are present in a smaller number of households like freezer, computer, stove, dryer, dishwasher, bread oven and pressure washer. The study reveals that some devices are present in multiple numbers. This is the case especially for refrigerators (1.1 units per household), TV's (1.3 units per household) and personal computers. Other devices are present with one unit per household. The level of household income influences the rate of possession as well as the use of electrical appliances. The same study concludes that people with higher incomes buy more appliances (for comfort, status, convenience, etc.). The size and type of households also plays a role in the possession of appliances. Large families with high number of individuals consume more energy than smaller ones. However, the more the family is large, the more devices are shared among individuals, and consequently the less is the energy consumption per person (Crioc, 2009).

A study conducted by Weber et al. (2000) on the impact of lifestyle factors on energy demand in Germany. The study reveals that ownership of domestic appliances is highly influenced by household characteristics. The authors distinguish home appliances between those continuously running, such as a refrigerator, and those that need a signal from the user, the so-called discrete appliances. For the major discrete appliances, the intensity of use is dependent on the size and type of the household. Weber et al. highlight that the explanatory power of various household's

factors depends directly on the appliances considered. For instance, they found that dishwasher ownership is most strongly influenced by household income. As for many of the other appliances (washing machine, tumbler, TV-set, cooling equipment and freezing equipment), household size has the highest impact. According to the study, household age is not found to be very influential on the ownership for major domestic equipments (Crioc, 2009).

A study conducted by Mansouri et al. (1996) in the UK reveals high correlations between socio-economic attributes of households and the equipment ownership. For instance, the authors conclude that refrigerator ownership level is highly dependent on households' income and socio-professional class. The same finding is also established for TV ownership rates. According to Mansouri et al., correlations between household attributes and ownership levels are also present for other domestic appliances such as washing machine, dishwasher, electric oven, microwaves and vacuum cleaners. Yun et al. (2011a). confirm that household income is an important factor in determining ownership of air conditioning equipments Another study of Nugroho et al. (2010) reveals that households' socio-economic attributes (income, household size, household type) have negative influence on refrigerator ownership. In contrast, the authors confirm that other household attributes, in particular age and education level, can influence positively the ownership of refrigerators.

3.1.3.2 Appliances energy-rating

Education level and environmental concern are the major reasons why people choose to purchase low-consuming home appliances. Mansouri et al. (1996) confirm that a clear relationship exists between the education level of households and the installation of energy efficient appliances in their dwelling. Households with higher education levels install low-energy bulbs and energy-efficient appliances more than less-educated households. Barr et al. (2005) confirm that the environmental concern is the major determinant in the purchasing energy-saving appliances such as washing machines, cookers, fires, and dishwashers. The income is also shown to be a determinant factor in purchasing energy-efficient equipments (Maresca et al., 2009). Grantham (2010) concludes that wealthier households tend to purchase more energy efficient services and appliances than poorer households. Economic reasons can also be behind the purchasing of energy-efficient equipments. Mansouri et al. (1996) highlight for example that low-consuming

bulbs were installed mainly for reasons of economy, since their energy consumption is limited, and thus their electricity cost is minimal.

3.1.3.3 Appliances size and quantity

The size of equipments and their number present in a dwelling are found to be mainly correlated to the dwelling size (surface area) and the household size (number of occupants). Some studies conclude also that income can affect the number of appliances with wealthier households having higher levels of equipment ownership than poorer ones (Grantham, 2010). Although in some studies, the number of domestic appliances owned is linked to the level of education held by head-of-household, this trend is likely to be a result of the positive general correlation between income and education level.

The multiple-appliance ownership within the same household is addressed in a number of studies. Multiple-appliance ownership indicates that within a household more than a single appliance is available for providing the same service. This is the case especially for refrigerators and televisions (Crioc, 2009; Mansouri et al., 1996; Yao and Steemers, 2005). For example, Mansouri et al. (1996).found that the average number of refrigerators in UK is 1.77 units per household. As for TVs, Mansouri et al. found it to be highly correlated to income and socio-professional class. In other studies such that in, equipments' multi-ownership is detected especially for refrigerators (average of 1.1 unit per household), TV's and VCD's (average of 1.3 units per household) and personal computers (average of 1.3 units per household) (Crioc, 2009). The same study concludes that when other devices are present in a household, their average number is one unit for each.

3.1.3.4 Appliances use trends

The use of home appliances can differ largely from one household to another according to occupants' attributes. Robert et al. (2012) conduct a study to track domestic appliances stock and their use patterns in Australian households. The study reveals some important features about equipment use patterns as a function of Australian households attributes. For example, the study examines the use pattern of dishwashers and washing machines as a function of occupants' features (household size particularly). The use of cloth washer and dishwasher is investigated by estimating the typical number of loads of washing a household do per week and per person. For

cloth washer, it is found that the number of loads per week increases with the household size (number of occupants) but decreases if we speak of rate per person. For example in one person households the average of 2.3 loads per week compares with 5.8 for 4 person households which is equivalent to just 1.5 loads per capita. This reflects the economies of scale emanating from larger household sizes. Same conclusions are drawn for dishwashers. Mansouri et al. conclude that the usage of dish-washer is not very different between different socio-economic groups (Mansouri et al., 1996). Morely et al. (2011) investigate the resources of variation in energy consumption between households in UK. The authors conduct a comparative analysis of electricity consumption in infrastructural homogeneous samples. They analyze occupants' practices such as TV watching, eating and drinking, working, and playing. For example, the study reveals that usage patterns of TV's (watching frequency and duration) can differ dramatically as a function of household's attributes preferences.

As a conclusion, literature emphasize the presence of high correlations between household attributes from one side and domestic appliances ownership levels, use patterns, their type and energy rating from the other side. A number of researchers highlight that statistically derived stochastic approaches provide a good methodology to simulate real consumption behaviors of buildings' occupants more accurately (Fischer and Kunz, 2004; Subbiah, 2013). Such probabilistic models are also applied in other research domains. For instance, Telenko (2012) uses Probabilistic Graphical Models (PGM) to represent the usage context as a network of factors characterized by local conditional probability distributions.

Therefore, developing stochastic relations between household-related determinants constitutes an important step towards modeling residential energy consumption. This will be the basic step of the modeling approach we are proposing in the following section.

3.2 A Stochastic Activity-Based Energy Consumption model proposal

As pointed out in our research objectives, we are not focused neither on modeling aggregated or typical behavior of building occupants, nor on dynamic models that calculate energy consumption on the basis of daily time-steps. However, we develop a parametric predictive model which takes a certain household profile with specific attributes as input and gives its corresponding energy consumption spectrum as output. The main advantages of such a model are its capability to reveal the variability in consumption values among different households, and to provide accurate energy demand spectrums as a function of households' attributes. Therefore, in this section, we propose a stochastic activity-based approach for modeling residential energy consumption at the occupant level (as shown earlier in Figure 3.2). Such an approach requires knowledge about occupants and their energy use patterns. Thus information regarding household's characteristics and their lifestyles are needed.

Activity-based approach means that the energy consumption of a household is estimated through summing up the energy use due to different activities performed. Activity quantities are quantified as a function of household attributes, and then translated into energy consumption values. Moreover, the stochastic nature of the model is due to the probabilistic mapping established between household attributes from one side (household type, number of occupants, etc.) and the corresponding appliance ownership, appliance characteristics and power rating, and activity quantities from the other side. In order to establish these probabilistic relations, a fairly sufficient number of households' characterizing attributes is taken into account, and statistically-derived relations are considered (refer to section 3.1.3).

The structure of the proposed SABEC (Stochastic Activity-Based Energy Consumption) model is represented in Figure 3.3, where its different objects are explained in the following. This model lies on two major hypotheses which are discussed further in this dissertation:

- First, for deriving an activity quantity per household from an estimation of the activity quantities per individuals, cumulative summation may be assumed for a given activity but of course the sharing of activity or economies of scale may diminish this basic summation.

- Second, activities in a dwelling must be enounced in such a way that they do not overlap on each other and the cumulative sum of energy consumed per each activity may be used to globally assess energy consumption of a household in a dwelling.

3.2.1 Households and individuals

The attributes describing individuals and households are chosen based on literature review and statistical studies (refer to chapter 2 and section 3.1.3). A household (*HH*) comprises one or more individuals living in the same dwelling and is characterized by a number of attributes. The characteristics of a household are represented mainly by those of its reference person (RP). The definition of reference person, household head or family head in some cases, is widely adopted in scientific literature (Barr et al., 2005; Druckman and Jackson, 2008; McLoughlin et al., 2012) and French national statistics (INSEE, 2012). Reference person is defined as the elder economically-active individual among household adults. These studies consider the reference person as the representative of a household's socio-economic status. Therefore, we adopt the same definition of reference person in our model.

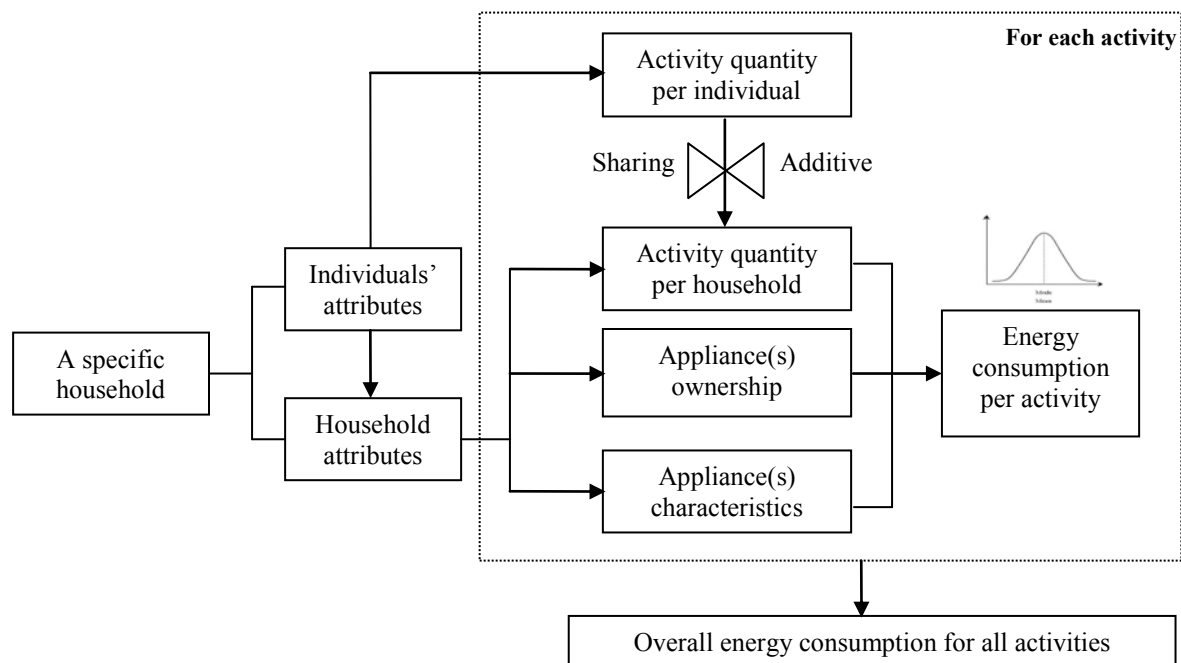


Figure 3.3: SABEC model architecture

Households and individuals are represented by a number of fundamental attributes (e.g. age, income, etc.) in addition to some intermediary attributes (e.g. awareness towards environment). Intermediary variables are introduced so that to account for some household characteristics and behavior towards energy consumption that cannot be understood directly from fundamental attributes. In the following, we present all variables that we consider representative of individuals and households, with a brief explanation of their influence on energy consumption.

Table 3.1: Households' and individuals' fundamental attributes

Individual attributes	Household attributes
Age	Household type
Gender	Number of adults
Activity status	Number of children
Socio-professional class	Household's total income
Education level	RP's age
Income	RP's activity status
	RP's socio-professional class
	RP's education level

3.2.1.1 Variables characterizing an individual

- **Age:** The age of an individual can exert a strong influence on energy consumption. Individuals perform different activities, purchase different equipments and have different comfort preferences according to their age. Age categories representing the French population are taken from the national institute of statistics and economic studies INSEE, and are presented in Table 3.2.
- **Gender:** energy consumption of an individual can differ according to his/her gender. Gender distribution of the French population is presented in Table 3.3.
- **Activity/Employment status:** The residential energy consumption is largely correlated to the activity and employment status. The latter influences directly the occupancy profiles of household's individuals, inducing thus a high impact on energy consumption trends. For

instance, un-employed individuals and retired people are logically more present at home than working individuals, performing thus more domestic activities and consuming more energy. For example, the presence at home affects the regulation of heating temperatures, increases the duration of activities such as cooking, watching TV, etc. Activity and employment status of the French population is presented in Table 3.4. The category of Inactive (15 to 24) refers to students, while inactive (> 65 years) refers to retired people, and other inactive category refers to children (<15 yrs), housewives, and non-capable inactive persons.

Table 3.2: Age categories of the French population (INSEE, 2013)

Age	Percentage share in the total population
Less than 26	30,5
26-35	12,3
36-45	13,3
46-55	13,6
56-65	12,7
66-75	8,6
> 75	9,1
Total	100

Table 3.3: Gender categories of the French population (INSEE, 2013)

Gender	Percentage share in the total population
Male	48,44
Female	51,56
Total	100 %

Table 3.4: Activity and employment status categories (INSEE, 2013)

Activity/employment status	Percentage share in the total population
Active-employed	51,3
Active-unemployed	5,2
Inactive (15 to 24 years)*	9,1
Inactive (>65 years)**	19,9
Other inactive***	14,5
Total	100 %

- **Education level:** as we take the reference person as representative of the family, the education level of a household is thus represented by that of its reference person. Education level is highly correlated to the professional status and income. In addition, the higher the education level is the higher is the environmental awareness of the household (Zainul Abidin, 2010). Education levels and their distribution among the French population are presented in Table 3.5.

Table 3.5: Education level categories (INSEE, 2013)

Education level	Percentage share in the total population
No diploma or CEP	26,2
Junior high school certificate	6,8
CAP (vocational training certificate), BEP	20,3
Baccalaureat, or equivalent	14,2
Short-term higher education	9,4
Long-term higher education	12,5
Pursuing initial studies	10,6
Total	100 %

- **Socio-professional class:** Energy consumption is highly correlated to the social and professional class of households (Santamouris et al., 2007; Yun and Steemers, 2011a). For instance, occupancy hours at home depend on individuals' working hours and so do domestic activity patterns. In addition, households' income levels are directly related to their professional status. The distribution of socio-professional classes of the French population is presented in Table 3.6.
- **Household income:** The income is a substantial determinant of households' energy consumption behavior. It has an impact on equipment ownership and energy consumption levels. Some studies show that the higher income of a household, the higher is the number of domestic appliances owned (Young, 2008). Moreover, it is logically evident to assume that households with higher incomes afford to consume more energy than those with lower

incomes who are restrained by their budget, and thus tend to reduce their consumption. The distribution of income categories per French individual is given Table 3.7.

Table 3.6: Socio-professional categories (INSEE, 2013)

Socio-professional category	Percentage share in the total population
Independent	5,95
Senior managerial staff	8,05
Middle level professions	11,90
Clerical and service staff	14,57
Manual workers	10,82
Total	100%

Table 3.7: Income categories per French individual (INSEE, 2013)

Monthly net income (Euros)	Percentage share in the total population
Less than 700	7,6
700-1000	11,6
1000-1500	20,8
1500-2000	17,4
2000-3000	24,9
3000-4500	13,1
More than 4500	4,6
Total	100

3.2.1.2 Variables characterizing a household

As mentioned earlier, the characteristics of a household are generally represented by those of its reference person. The other attributes are household type, number of occupants and household's income.

- **Household type:** Household type represents the family structure. According to national statistics, the French population is classified into the following household types: Singles, couples with children, couples without children, one-parent households, and other households (Table 3.8). Energy consumption varies among households as a function of the number of individuals and their age (adults and children). Therefore, energy consumption levels will of

course vary as a function of the household type. Clustering population into different family types is important for assessing variation in consumption between patterns between families having the same number of individuals but with different structure.

Table 3.8: Household types (INSEE, 2013)

Household type	Percentage share in the total population
Singles	33,5
Couples without children	26,1
Couples with at least one child	27,4
One-parent households	7,9
Composite households	5,1
Total	100

- **Number of occupants:** it is a major determinant of energy consumption in dwellings. Households with higher number of occupants will logically show higher occupancy levels and will perform more energy-consuming activities, leading thus to higher energy consumption levels. Energy consumption can differ between children and adults of same household. This difference is taken into account through the “age” variable.
- **Household income:** is the total income of the household. It is calculated by summing up the incomes of all active employed individuals within the household.
- The remaining representative attributes of a household are those of its reference person. These are: reference person’s age, activity/employment status, education level, and socio-professional class.

In addition to the preceding fundamental variables, we introduce an important intermediary variable namely the environmental awareness. Environmental awareness represents individuals’ attitudes towards purchasing energy efficient appliances as well as their energy consumption patterns. Literature review and statistical studies show that the environmental awareness of a household is directly influenced by three main attributes which are the age, income and the education level (Barr et al., 2005; Maresca et al., 2009).

Environmental awareness: can affect appliance ownership levels as well as energy consumption behavior of occupants. For instance, an energy-conscious individual would rather prefer to buy low-energy consuming appliances, and will apply certain energy-efficient habits such as turning off light when not necessary. The classification of environmental awareness levels is adopted from a French study which distribute environmental awareness into different levels ranging from 1 to 5 (Maresca et al., 2009). High environmental awareness (HEA) corresponds to levels 4 and 5, while low environmental awareness to levels 1, 2 and 3 (Table 3.9). According to Maresca et al. (2009), the environmental awareness level of a given household is mainly influenced by three determinants: household's total income, reference person's age, and reference person's education level.

Table 3.9: Environmental awareness levels [from (Maresca et al., 2009)]

Level	Environmental awareness
1	Very little aware
2	Little aware
3	Moderately aware
4	Enough aware
5	Very aware

People with higher environmental awareness levels (levels 4 and 5) are more conscious to sustainable development and more respectful to energy reduction policies. They possess mainly energy efficient appliances and they often try to limit energy squandering.

3.2.2 Mapping household attributes to appliance ownership and characteristics

The second part of the model consists of establishing relations between households' attributes exposed above, and the ownership of home appliances as well as their characteristics. For this sake, we use national statistical data of appliance ownership in addition to other sources of information regarding equipments characteristics (energy rating, technology, etc.). These features of the model are exposed in this section while their demonstration is better identified through model applications in chapters 4 and 5.

3.2.3 Quantifying an activity

In order to quantify a given activity, we define a quantification unit namely the “service unit”. This definition is based on the definition of the functional unit in Life Cycle Assessment (ISO 14044). For example, we define the service unit of the activity “watching TV” to be the duration in minutes per household per day, and that of the activity “washing clothes” as the quantity of clothes to be washed per month. As pointed out earlier and exposed through SABEC model’s architecture (Figure 3.3), we disaggregate an activity’s quantity to both households’ and individuals’ levels as a function of their socio-demographic and economic attributes. Therefore, the service unit of an activity is determined basically per individual. The household’s service unit for an activity can thus be determined through aggregating the service units of all household members. This depends on the nature of the considered activity, whether it can be shared by household members or not.

3.2.3.1 Activity nature

The nature of a domestic activity determines the way how it can be quantified. We distinguish here two types of activities: additive and shared (Table 3.10). An activity is said to be shared if its service unit can be shared by two or more household members. For instance, watching TV is considered as a shared activity since, in most cases, family members watch TV together. Thus the total service unit of this activity at the household level is not the sum of all individual activities, but it is rather an aggregated sum with a percentage of sharing. Shared activities may also be carried out individually. On the other side, an activity is said to be additive if its service unit at the household level is the sum of all individual service units. In this case, sharing does not take place. For instance, using computers and bathing are two additive activities.

It must be noted here, that we consider the sharing and non-sharing as a function of the activity’s service unit, and not as a function of the appliance. In other words, people may share the same appliance for the same activity; however they do not share the service unit. A direct example of this is the “washing laundry” activity. The service unit of this activity is defined as the “quantity of laundry” generated per month. In general, household members use the same washing machine at home, yet their service units are not shared. Each person uses his/her own laundry in a different way than others.

Table 3.10: Examples of some activities' nature and service units

Activity name	Service unit	Activity nature
Watching TV	Duration (min/time interval)	Shared/additive
Washing clothes	Quantity of laundry produced (Kg)	Additive
Bathing	Number of showers	Additive
Washing dishes	Quantity of dishes produced (volume)	Shared/additive
Using computer	Duration	Additive
Ironing	Quantity of laundry	Additive
Eating	Number of meals	Shared/additive
Drying clothes	Quantity of laundry	Additive
Video games	Duration (min/time interval)	Shared/additive
Cooking	Duration/intensity	Shared/additive

3.2.3.2 Cascading of service units between activities

Domestic activities can interact with each other reciprocally. Some activities may be carried out simultaneously by household members. The most common example of that is watching TV while eating in the evening. An activity may provoke other activities on one hand, while being influenced by other activities on the other hand. This yields to an influence of the service unit and thus on energy consumption. For instance, eating and cooking activities provoke the “washing dishes” activity and influences its service unit. Therefore, when quantifying the total energy consumption of overall activities, such interactions must be taken into account.

3.2.4 Example application (guiding example)

In order to clarify the above proposed activity-based model, we expose here a brief demonstration on the “Watching TV” activity. The modeling frame work for the activity “watching TV” is shown in Figure 3.4. In order to determine the energy consumption yielded by this activity for a given household, a number of steps are followed:

- First, the ownership rate (probability) of the TV appliance is determined as a function of household's attributes. This can be done based on French national statistics of appliance ownership.

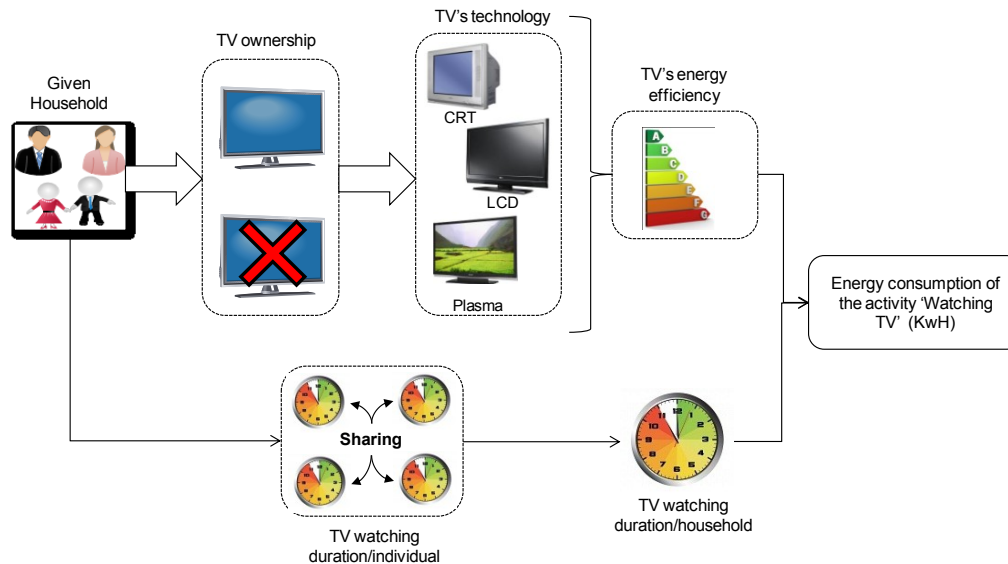


Figure 3.4: Modeling logic for quantifying the energy consumption of the activity “watching TV” for a given household

- Second, knowing that TV’s can exist in multiple technologies and energy rating, these can be determined in form of probabilities based on national distributions. Once the technology of the owned TV is determined, its power rating can thus be deduced.
- Third, the service unit for this activity is defined to be the watching duration in minutes per day. This service unit can be taken from national statistical surveys giving watching duration of TV per individual per day. Knowing that household individuals can watch TV simultaneously, we must take into account a sharing percentage between the watching durations. To account for this sharing coefficient, we can either use statistical data (if there any) or define aggregation heuristic logics to be validated through comparison with real measured data, or through experts opinions.
- Finally, by using the service unit together with the power rating of the appliance, the energy consumption yielded by the “watching TV” activity can be estimated.

The preceding example on the activity “watching TV” is presented here shortly only for the purpose of exposing our proposed SABEC model. Later in chapters 4 and 5, detailed applications of the model are demonstrated on two activities (watching TV and washing laundry). In these two chapters, details about the choice of variables, the statistical data used, the quantification

mechanisms of service units and energy consumption are given. Simulation examples of the yielded energy consumption are also performed, and both models shall be validated.

3.3 Modeling and simulation flows of the SABEC model

In this section, we expose the detailed structure of the proposed SABEC model. The probabilistic relations between model's objects are presented together with all statistical data their nature sources and the way they are integrated into the model. As discussed in the previous section through Figure 3.3, the model takes households' attributes at the input. The first step is to determine the intermediary "environmental awareness" variable.

3.3.1 Determining environmental awareness level of a household

We consider the environmental awareness level of a household, denoted by EAL_{HH} , as a function of three determinant variables which are household's total income, denoted by I_{HH} , reference person's education level, denoted by EL_{RP} , and reference person's age, denoted by AG_{RP} . Maresca et al. (2009) give probability distributions of households having high environmental awareness (levels 4 and 5), denoted by (HEA), as a function of each of these three variables. These marginal conditional probabilities are shown in Table 3.11, Table 3.12, and Table 3.13. Consequently, the joint probability of a household to have a high environmental awareness, denoted by $P(HEA_{HH})$, can thus be estimated through these three marginal probabilities.

As shown in Figure 3.5, the probability of having a high environmental awareness $P(HEA_{HH})$, is estimated by calculating the joint probability of the three previously mentioned individual probabilities.

Table 3.11: Environmental awareness given age (Maresca et al., 2009)

Age of reference person AG_{RP}	Probability of having high environmental awareness (Levels 4 and 5) $P(HEA/AG_{RP})$
Less than 25	0.27
26-35	0.42
36-45	0.44
46-55	0.40
56-65	0.45
66-75	0.45
More than 75	0.30

Table 3.12: Environmental awareness given income (Maresca et al., 2009)

Income level (net monthly) I_{HH}	Probability of having high environmental awareness (Levels 4 and 5) $P(HEA/I_{HH})$
Less than 700	0.32
700-1000	0.33
1000-1500	0.33
1500-2000	0.42
2000-3000	0.43
3000-4500	0.51
4500 or more	0.50

Table 3.13: Environmental awareness given education level (Maresca et al., 2009)

Education level EL_{RP}	Probability of having high environmental awareness (Levels 4 and 5) $P(HEA/EL_{RP})$
No education, CEP	0.30
BEP, CAP	0.35
BAC	0.42
BAC +1, BAC +2	0.52
BAC +3, BAC +4	0.51
BAC +5 and more	0.60

The formula used for calculating the joint conditional probability $P(A|D_i)$ of an event A given three (or more) dependant events D_i ($i = 1, \dots, n$) is adopted from (Journel, 2002) and presented in equation 3.1.

$$P(A | D_i, i = 1, \dots, n) = \frac{1}{1 + x} \in [0, 1] \quad (3.1)$$

$$\text{With } x = \frac{\prod_{i=1}^n d_i}{a^{n-1}} \geq 0$$

$$\text{and } a = \frac{1 - P(A)}{P(A)} ; d_i = \frac{1 - P(A|D_i)}{P(A|D_i)}, i = 1, \dots, n$$

Hence, $P(HEA_{HH})$ can thus be calculated as shown in equation 3.2:

$$P(HEA_{HH}) = P(HEA | AG_{RP}, I_{HH}, EL_{RP}) \quad (3.2)$$

During simulation (as will be explained later in this chapter): Once $P(HEA_{HH})$ is calculated from equation 3.2, a random number (R_1) is generated uniformly (through Monte Carlo technique) to determine the environmental awareness level (EAL_{HH}) of a given household according to Table 3.14.

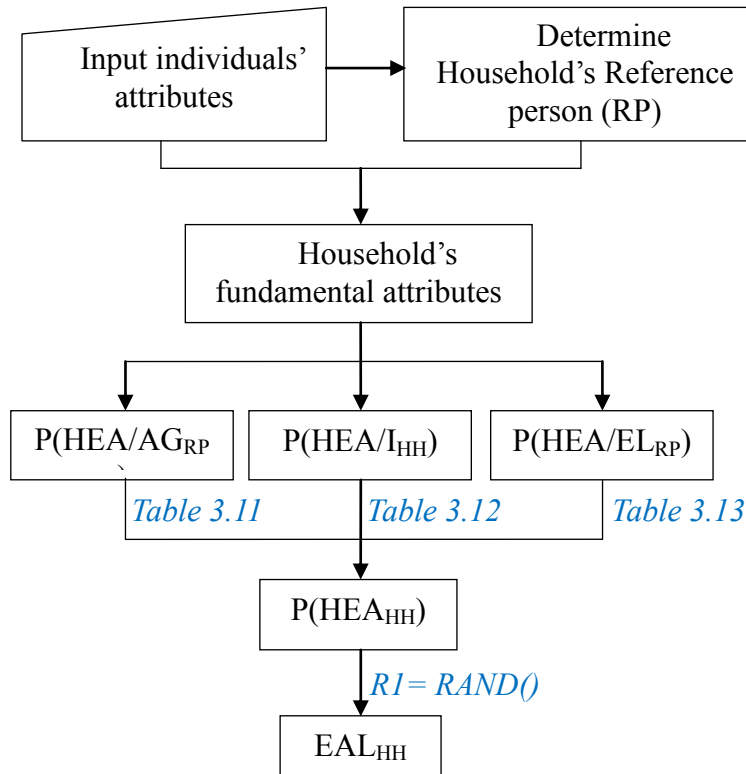


Figure 3.5: Determining environmental awareness level

Table 3.14: Random process for determining the environmental awareness level of a household

Condition of the random variable R_1	Environmental awareness level (EAL_{HH})
$R_1 < (P(HEA_{HH})/2)$	5
$R_1 < P(HEA_{HH})$	4
$0 < ((R_1 - P(HEA_{HH})) / (1 - P(HEA_{HH}))) < 0,33$	3
$0,33 < ((R_1 - P(HEA_{HH})) / (1 - P(HEA_{HH}))) < 0,66$	2
$0,66 < ((R_1 - P(HEA_{HH})) / (1 - P(HEA_{HH}))) < 1$	1

3.3.2 Mapping household attributes to appliances' ownership and appliances' characteristics

3.3.2.1 Determining ownership rate of an appliance

We consider household's ownership rate of an appliance as a function of three main variables which are household type, denoted by HH_{Type} , reference person's age, denoted by AG_{RP} , and reference person's socio-professional class, denoted by SPC_{RP} . The conditional probability of having an appliance given each of these three variables separately is taken from national French statistics ((INSEE, 2010). These marginal probability distributions are shown in tables Table 3.15, Table 3.16, and Table 3.17. Consequently, the joint probability for a household to possess an appliance, denoted by $P(AP)$, can thus be estimated as shown in equation 3.3 and Figure 3.6.

$$P(AP) = P(AP | HH_{type}, SPC_{HH}, AG_{RP}) \quad (3.3)$$

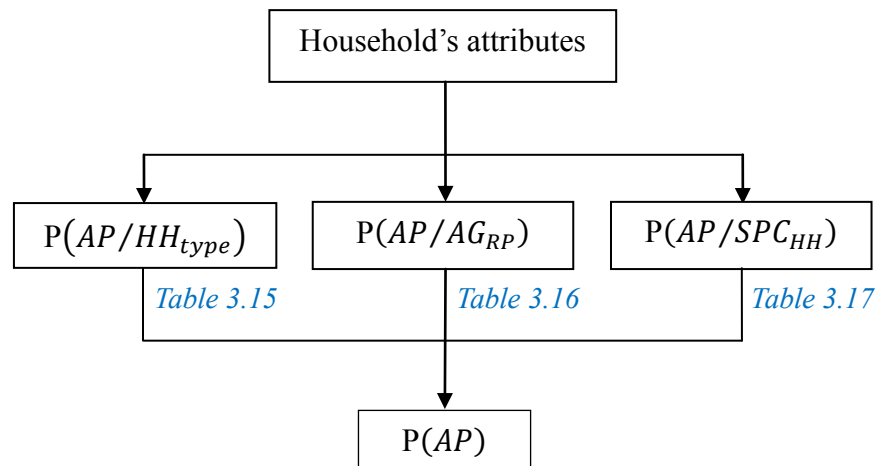


Figure 3.6 : Determining ownership rate of an appliance

Table 3.15: Appliance ownership rate (%) as a function of household type (INSEE, 2010)

Appliances	$P(AP/HH_{type})$				
	Single	One-parent family	Couples without children	Couple with one children or more	Other households
Refrigerator	99,4	100	100	100	100
Freezer	76,3	88,9	92,8	94,7	88,7
Micro-wave oven	76,1	90,5	86,1	93,7	87,6
Cloth washer	87,5	98,8	98,5	99,6	93,5
Dishwasher	27,2	46,6	63,8	72,1	42
Color TV	95,3	98,6	98,8	98,7	97,8
VCD, DVD player	69,7	88,4	87,6	95,4	83,8
Landline phone	83,2	82,6	94,3	93,3	89,4
Mobile phone	64	90,4	82,6	95,7	81
Computer	45,8	77,7	63,1	92,9	68,8
Internet	39	69,1	57,7	87,6	60,1

Table 3.16: Appliance ownership rate (%) in function of age (INSEE, 2010)

Appliances	$P(AP/AG)$				
	16-24	25-39	40-59	60 or more	Total
Refrigerator	99,7	99,8	99,7	99,9	99,8
Freezer	64,3	84,6	90,4	88,2	87,3
Micro-wave oven	93,8	90	89,9	76,3	85,2
Cloth washer	80,2	93,8	96,8	95,4	94,9
Dishwasher	18,9	49,8	59,1	48,6	51,6
Color TV	96,2	95,8	97,3	99	97,5
VCD, DVD player	83,7	90,1	91,4	71,7	83,6
Landline phone	61,5	83,1	90,4	94,9	89,2
Mobile phone	91,2	92,8	90	61,3	80,4
Computer	85,4	89,9	80,4	35,6	66,7
Internet	73,1	82,3	74	31,1	60,5

Table 3.17: Appliance ownership rate (%) as a function of socio-professional class (INSEE, 2010)

Appliance	$P(AP/SPC_{RP})$							
	Farmers	Craftsmen, traders	Senior managerial staff	Middle level professions	Clerical and service staff	Manual workers	Retired	Other inactive
Refrigerator	100	99,3	100	100	99,5	100	99,8	99,3
Freezer	93,9	90	87,4	85,8	84,7	86	87	73,8
Micro-wave oven	86,2	91,9	84,3	89,6	91,4	89,7	74,6	75,9
Cloth washer	99,3	97,7	95,1	93,6	92,7	93,7	95,2	85
Dishwasher	69,6	76,2	65	55,9	37,2	42,3	46,5	28,2
Color TV	100	96,5	94,9	97	98,4	98,5	99,3	97,2
VCD, DVD player	87	86,1	91,3	91,5	90,2	89,9	73	68,6
Landline phone	89,1	86,1	96,7	90,8	85,3	83,4	94,9	83,3
Mobile phone	90,2	94,3	97,1	97,7	95,2	92,5	66,6	73,5
Computer	74,5	88,3	98,8	93,9	81,9	77,5	40,6	49,7
Internet	64,3	80,7	95,7	87,9	75,2	71,2	37,2	44,2

3.3.3 Determining appliances characteristics

Each appliance is characterized by its technology and energy rating. For example, a television may have a plasma or LCD technology. As for the energy rating, it represents the power (in Watts) consumed by the appliance when in use.

3.3.3.1 Appliance's energy efficiency

A domestic appliance is said to be energy-efficient if it consumes less-energy than other devices providing the same function or service. The energy efficiency of an appliance is rated in terms of a set of energy efficiency classes from A to G on the label, A being the most energy efficient, G the least efficient. A number of energy efficiency grades such as A+, A++ and A+++ were introduced for various products since 2010 (ECDGE, 2013). An important French study conducted by Maresca et al. from CREDOC⁴, the French research centre for the study and monitoring of living standards, provides some insights on equipments possession within French households (Maresca et al., 2009). The study being conducted in 2009, defines energy-efficient (or low consuming) appliances as those having class A labels, knowing that new labels were introduced later. The study concludes that the possession of energy-efficient appliances is influenced by three main determinants: the reference person's age AG_{RP} , households' income I_{HH} and household's environmental awareness level EAL_{HH} . In our model, we use these findings together with the statistical data collected.

The conditional probability of having an energy-efficient appliance given each of these variables separately is taken also from the study of Maresca et al. (2009) from CREDOC. These marginal probability distributions are shown in Table 3.18, Table 3.19, and Table 3.20. Consequently, the joint probability for a household to possess an energy-efficient appliance, denoted by $P(EAP)$, can thus be estimated as shown in equation 3.4 and Figure 3.7.

$$P(EAP) = P(EAP | AG_{RP}, I_{HH}, EAL_{HH}) \quad (3.4)$$

⁴ An important French study conducted by Maresca et al. (2009) from CREDOC, the French research centre for the study and monitoring of living standards, provides important insights on equipments possession and energy consumption trends within French households.

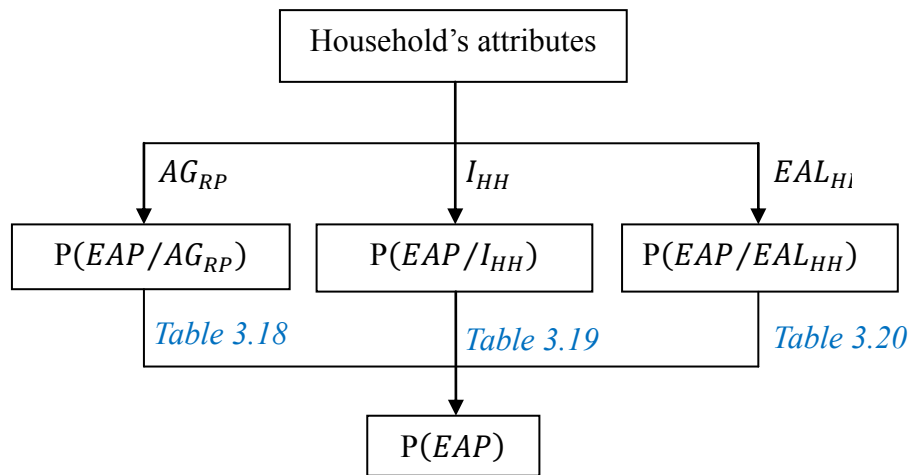


Figure 3.7 : Determining appliance's energy efficiency probability for a household

Table 3.18: Probability of having an energy efficient appliance given the age (Maresca et al., 2009)

Age group	Probability of having an energy efficient appliance given age $P(EAP/AG_{RP})$
< 25	0.50
26-35	0.67
36-45	0.70
46-55	0.65
56-65	0.66
66-75	0.54
> 75	0.30

Table 3.19: Probability of having an energy efficient appliance given the income (Maresca et al., 2009)

Income	Probability of having an energy efficient appliance given income $P(EAP/I_{HH})$
700-1000	0.31
1000-1500	0.50
1500-2000	0.62
2000-3000	0.70
3000-4500	0.80
4500 or more	0.70

Table 3.20: Probability of having an energy efficient appliance given the environmental awareness level (Maresca et al., 2009)

Environmental awareness level	Probability of having an energy efficient appliance given environmental awareness level $P(EAP/EAL_{HH})$
1	0.36
2	0.51
3	0.59
4	0.67
5	0.64

3.3.3.2 Determining appliance's quality (Technology)

The quality or technology type of domestic appliances is correlated to household attributes (Morley and Hazas, 2011). However, due to the non-availability of such statistical information for domestic appliances in France, we do not account for these correlations in the model. However, we simplify the issue by taking population-wise national statistics of appliances' technology types present in French dwellings. This point is further discussed while applying the model on two domestic activities through chapters 4 and 5.

3.3.4 Mapping individuals' attributes to activity quantities

The quantification of a given activity is done through what we called service unit (section 3.2.3) As discussed earlier in section 3.2.3, some domestic activities are additive, meaning that the service unit of the household is simply the sum of service units per individual. However, for some activities where "Activity-sharing" can take place (such as watching TV) the service unit is no more additive, and hence a sharing part must be taken into account. This sharing part can be accounted for either by using statistical data, if there any, or by defining heuristic logics, expressing the degree to which people of a household share an activity. This yields to the estimation of the total service unit of the household for a given activity, denoted by (ASU_{HH}) , as shown in Figure 3.8.

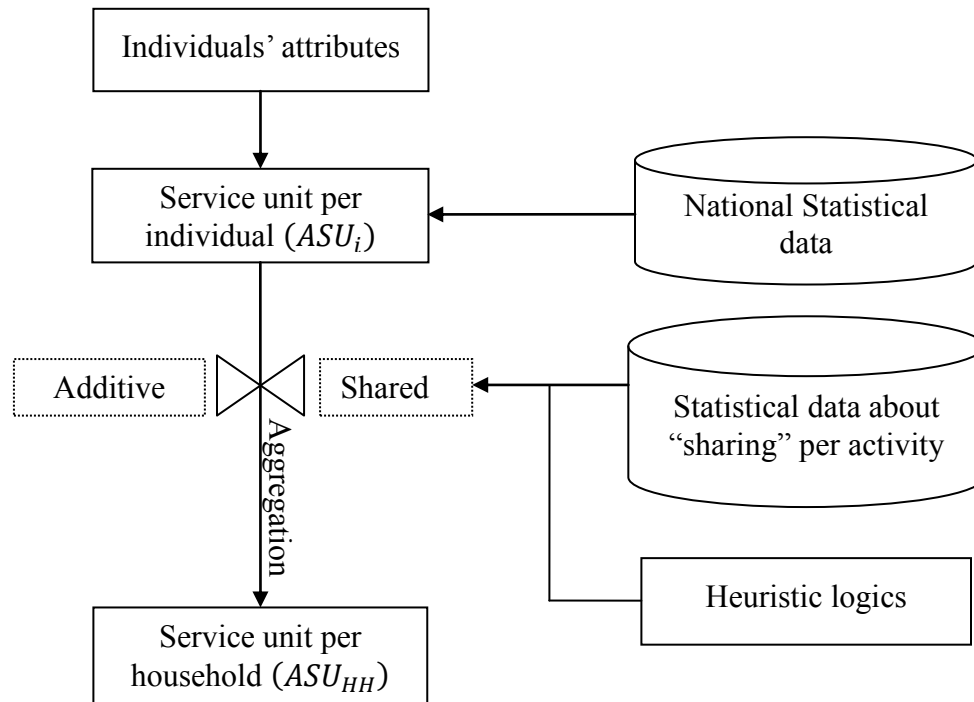


Figure 3.8 : Determining the service unit of an activity

3.3.5 Determining energy consumption for an activity

The energy consumption of an activity for a given household is estimated based on all the variables already explained in the preceding sections. Given the probabilistic nature of the model variables, **Monte-Carlo technique** is used to run simulations. At each simulation run, all random variables are re-initialized to determine deterministic values which are then used in the calculation. The number of simulation runs of the model is determined according to the convergence of the results. During each simulation run, random variables are generated to calculate: (1) the ownership of appliances (AP) (2) the environmental awareness level of the household (EAL) (3) the energy-efficiency of appliances (EAP), and (4) the appliance technology. The energy consumed by an activity for a given household, denoted by AEC_{HH} , is thus calculated stochastically as a function of the service unit ASU_{HH} and the power rating P of the appliance involved as shown in Figure 3.9.

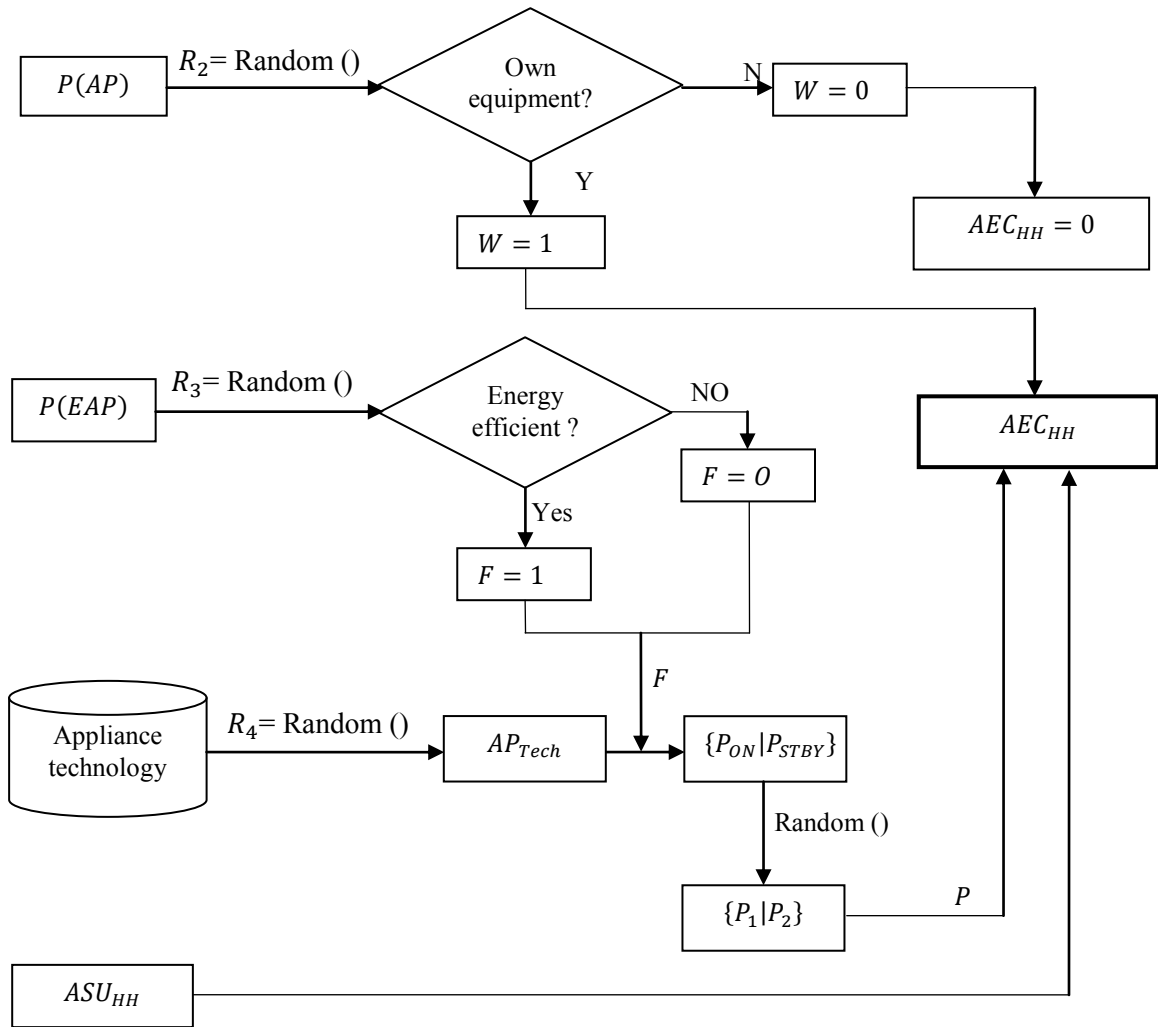


Figure 3.9 : Determining energy consumption of an activity

AEC_{HH} is the energy consumed by a household for carrying out a given activity. W represents the possession of an appliance determined by generating a random variable R_2 as shown in Table 3.21. F represents the energy efficiency of the appliance determined by generating a random variable R_3 as shown in Table 3.22. P is the power consumed by the appliance which is chosen randomly from power rating intervals coming from statistical data ($P = P_1$ for ON mode and $P = P_2$ for standby mode). ASU_{HH} is the household's aggregated service unit.

Table 3.21: Random process for determining appliance ownership

Condition of the random variable R_2	Value of W	Appliance ownership
$R_2 \leq P(AP)$	$W = 1$	Own appliance
$R_2 > P(AP)$	$W = 0$	Do not own appliance

Table 3.22: Random process for determining appliance's energy-efficiency

Condition of the random variable R_3	Value of F	Appliance's energy-efficiency
$R_3 \leq P(EAP)$	$F = 1$	Energy-efficient
$R_3 > P(EAP)$	$F = 0$	Non energy-efficient

The overall simulation flow for calculating energy consumption of an activity for a given household is presented in Figure 3.10. The final energy consumption yielded by an activity is thus estimated as shown in equation 3.5.

$$AEC_{HH} = W \times F \times P \times ASU_{HH} \quad (3.5)$$

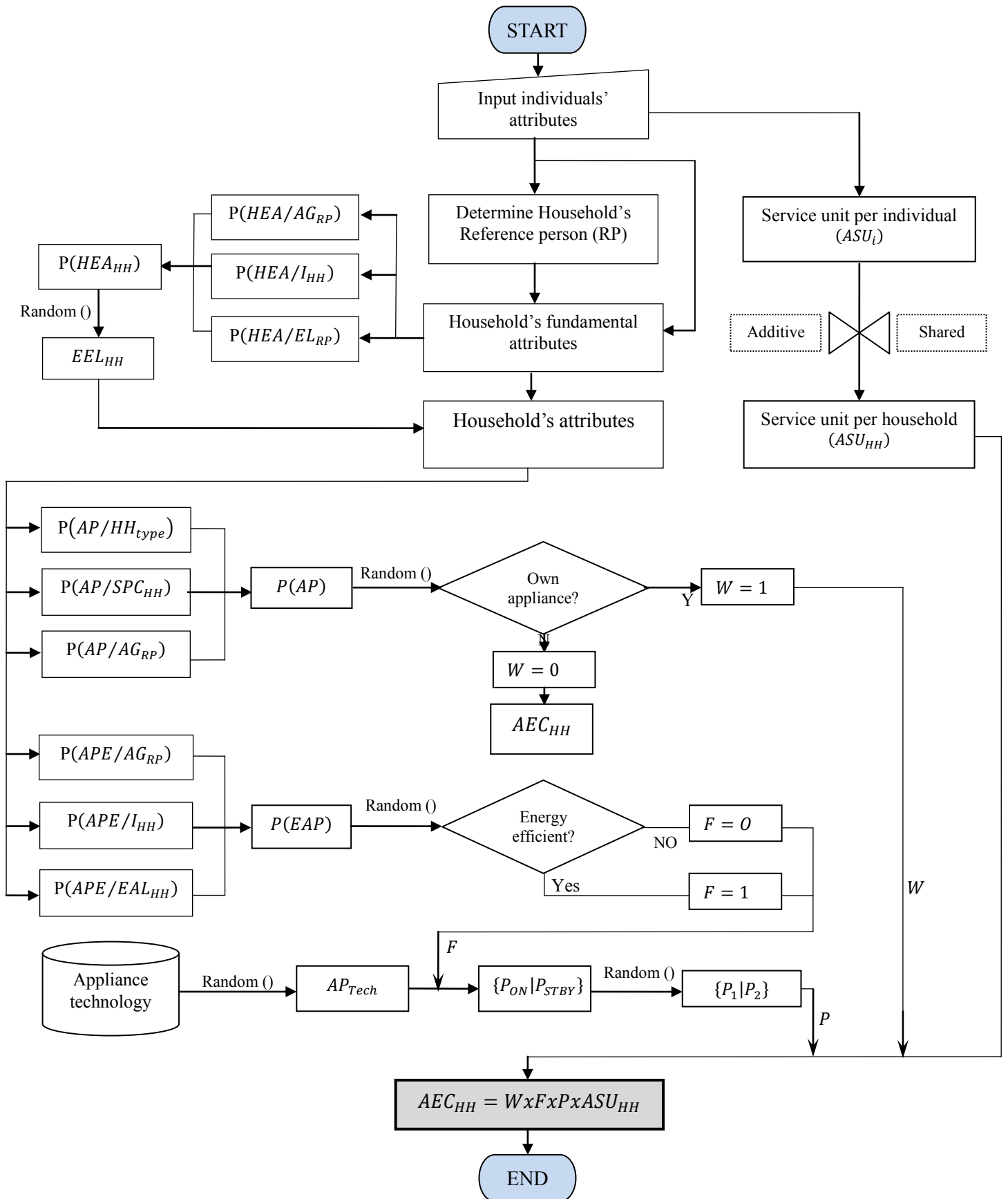


Figure 3.10: Overall simulation flow for calculating energy consumption of an activity for a given household

3.4 Model application

The SABEC model proposed in this third chapter is applied afterwards on two domestic activities, namely “watching TV” in chapter 4 and “washing clothes” in chapter 5. The reasons for choosing these two activities as case studies are discussed within each respective chapter. The application of the SABEC model is performed in order to (1) test model functionalities and its ability to simulate energy consumption of domestic activities (2) reveal modeling difficulties which can be encountered such as the choice of activity’s determinant variables and the quantification of activity service units, and to (3) validate the model by comparing its simulation results to real data.

3.5 Model implementation

The proposed model was first implemented through simple interfaces on a Microsoft Excel work book. The statistical data used and the calculation mechanisms are included to provide simulations for specific households. The Excel work book may be user-configured or incorporated into other models as required. In addition, for the sake of creating very large data sets and to reduce calculation time-cost, the model was implemented in Python language. The computer model comprises, for now, only the two activities “washing laundry” and “watching TV”. Yet, it is structured in a way that any other activity can be added on the same architecture. A graphical user-friendly interface is developed on a host website to facilitate the usage and the communication of model functionalities.

Chapter 4: Application of SABEC model for the “watching TV” activity

In this chapter, we apply the proposed stochastic activity-based energy consumption model (SABEC) on the domestic activity “watching TV”. First, we give a description of this activity and we expose the reasons behind choosing it as a case study. The modeling steps of the activity are then presented in accordance with the SABEC model. The choice of model variables and the statistical data used as well as their nature and sources are presented and discussed. We perform a number of simulation examples in order to test the functionalities of the model. Simulation results are used to assess and interpret energy consumption variation between different households. Finally, we validate the model by testing the statistical significance of simulation results against real consumption data.

4.1 Introduction

Audiovisual devices consume an average of 470 KWh/year per French household (ADEME, 2012b) . This value represents about 20 % of the total electricity consumption of a French dwelling if we exclude hot water and heating (ADEME, 2012b). In recent years, energy consumption of audiovisual devices is not ceasing to increase due to their growing presence within dwellings. Among the most energy consuming audiovisual appliances are the televisions which are present in almost every French home. The average electricity consumption of televisions per household has increased sharply in recent years. Between 1995 and 2008 this consumption was multiplied by 2.2 times increasing thus from 140 to 307 kWh / year (ADEME, 2012b).

The electricity consumption of a television can differ according to its technology. For instance, LCD and plasma televisions consume respectively 1.8 times and 3.5 times more than CRT TVs whose screens are smaller (ADEME, 2012b). Like all electric equipments, especially audiovisual devices, a TV consume energy even when not in use. This energy consumed during the standby mode represents about 20 % of the total consumption of a TV device (Enertech, 2008).

The usage pattern of televisions can also differ largely among different households (Morley and Hazas, 2011). A French study concludes that usage duration of TV appliances can range

from zero to 9 hours daily among French households (Enertech, 2008). Households with different socio-demographic and economic attributes have different ownership rates (possession of TV's and their number) and of course different usage habits. A television at home can be used in different contexts. For instance, one can use it for watching broadcasted channels, watching DVD movies or for playing video games. In addition, a television can be used by a single individual or it can be used simultaneously by multiple household members. Hence, we talk about appliance and activity sharing. Given this complexity of sharing "TV watching" activity and the growing importance of audiovisual in electricity consumption, it has been chosen to be a case study for applying our proposed SABEC model.

In this chapter, a definition of the activity "watching TV" and description of the modeling logic are first presented. The process for determining activity's energy consumption using the SABEC model is then described. The steps for defining activity's service unit and for considering sharing logics among individuals are exposed. Later, simulation examples are performed on a number of households where different functionalities of the model are demonstrated: (1) Calculating energy consumption for a specific household (2) for a cluster of households having common input attribute(s) to study variability among them and (3) for a random population of households to have a representation of the whole population. The results of these simulations are then presented, discussed, and validated against real consumption data.

4.2 Modeling "Watching TV" activity

In this section, we describe the steps of modeling "watching TV" activity. In order to facilitate the understanding of modeling and simulation flows, step by step calculations are performed by taking two households as guiding examples. Household 1 is a single-parent family with 2 children and household 2 is a couple without children. The attributes of these households are summarized in Table 4.1.

4.2.1 Description of activity "watching TV"

In general, using TV at home encompasses a number of different activities. One can use television to watch broadcasted channels or DVD videos, to play video games, to listen to radio, or even to surf internet in case if the appliance is connected to the network (Figure 4.1). We define here the activity "watching TV" to be: Use a TV appliance for watching TV

channels and/or DVD videos. This definition is made in accordance with that used in national French time-use surveys (INSEE, 2012). The latter gives statistical data of mean use duration of TV appliances per day in French households. It computes this duration for both use cases: using TV to watch broadcasted channels and to DVD videos.

Sometimes people watch TV through their computers, tablets and their smart phones; however we do not take these usages into consideration in this activity since they can be considered in other activities. For example, using TV for video games shall be taken in another activity called “video games”. In addition to that, using the TV in order to surf internet and listen to radio are almost negligible among the five use cases.

Table 4.1: Description of the two guiding household examples

	Household 1	Household 2
Adult 1 age	34	45
Adult 1 gender	Female	Male
Adult 1 Activity status	Active	Active
Adult 1 SPC	Middle level profession	Senior
Adult 1 Education level	Baccalaureate	Long-term higher education
Adult 1 income	1400	3000
Adult 2 age	---	38
Adult 2 gender	---	Female
Adult 2 Activity status	---	Active
Adult 2 SPC	---	Middle level profession
Adult 2 Education level	---	Short-term higher education
Adult 2 income	---	1800
Children 1 age	5	---
Children 1 gender	Male	---
Children 2 age	8	---
Children 2 gender	female	---

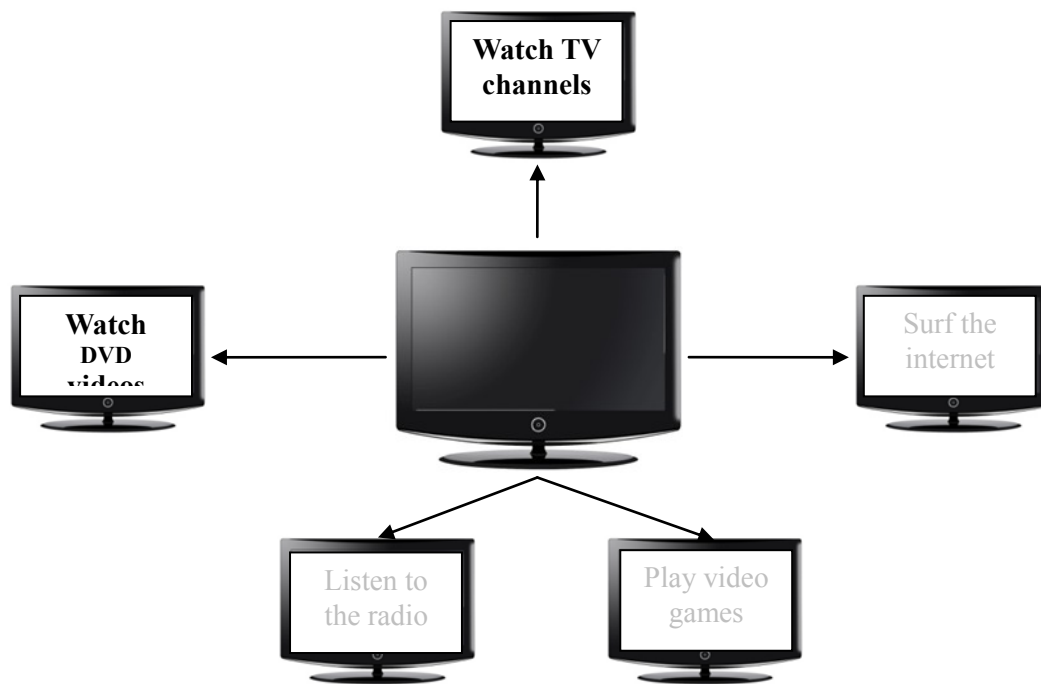


Figure 4.1: Different usages of a TV appliance (only bold usages are considered)

The two appliances included in the activity are televisions and DVD players. However, DVD players consume much less energy than televisions (EnerTech, 2008). The mean annual electricity consumption of televisions per French household is around 307 KWh/year, while for DVD players it does not exceed 19 KWh/year. The low consumption value of DVD players is due to their low power rating (10 W), as well as their rare and low use durations by household members. Due to these facts, we decide in a first modeling to neglect the impact of DVD player devices and we consider in the modeling of activity “watching TV” the sole TV appliances.

4.2.2 Determining ownership rate of TV appliances

For calculating ownership rates of appliances, national statistical data are used from (INSEE, 2010) (section 3.3.2). The probability that a household possesses a TV device is denoted by $P(TV)$. It is computed by using equation 4.1, which was presented earlier in chapter 3 (section 3.3.2.1).

$$P(TV) = P(TV | HH_{type}, SPC_{HH}, AG_{RP}) \quad (4.1)$$

Therefore, we calculate TV ownership for the two household examples by using equation 4.1. The results are summarized in Table 4.2.

Table 4.2: Appliance ownership probabilities calculated for two households

	Household 1(Single-parent family)	Household 2 (Couples without children)
Reference person	Adult 1	Adult 1
$P(AP/HH_{type})$	0,98	0,98
$P(AP/SPC_{RP})$	0,97	0,94
$P(AP/AG_{RP})$	0,95	0,97
$P(AP)$	0,97	0,99

4.2.3 Determining TV appliance characteristics

We consider that a TV device is characterized by its technology and power rating.

4.2.3.1 TV technology

An important study⁵ conducted by Enertech (2008) assess TV technologies present in French households. According to this study, three main TV technologies are identified: cathode ray tube (CRT) screens, liquid crystal displays (LCD) screens and plasma screens. The distribution of these technologies is given in Table 4.3. Therefore, we use the results of this study to consider TV technologies. The correlation between household attributes and the corresponding appliance technology is not easy to establish due to the non-availability of data sources needed. Hence, to allocate a given TV technology for a given household, we use directly the global population-wise distribution shown in Table 4.3. During simulation, a uniform random variable is generated through Monte Carlo technique and is then used to determine appliance's technology for a given household (Figure 4.2).

4.2.3.2 Appliance energy rating

The energy rating of a TV represents its energy consumption. An energy-efficient appliance normally consumes less energy than a non-efficient one. The distribution of power ratings of

⁵ The REMODECE project is a European data collection and policy support activity in the EU27 area. The project aims at improving the understanding of the structure and trends of domestic electricity demand, factors underlying it, and its implications for policy making in the European Union region (Remodece, 2008).

TV's is taken from the study conducted by (Enertech, 2008). For each TV technology, appliances may be energy efficient or not. The classification of TV's to energy efficient and non-energy efficient is made according to their power rating (Table 4.4). Televisions of CRT technology are considered to be non energy-efficient because of their high power rates (Enertech, 2008). P_{ON} represents the power of the appliance when switched ON, while P_{STBY} is the power when the appliance is in standby mode. According to (Enertech, 2008), the most energy-efficient TV's are those equipped with LCD technology.

Table 4.3: Distribution of TV technologies present in French households (Enertech, 2008)

TV technology	Distribution population
CRT	28
LCD	37,6
Plasma	34,4
Total	100 %

Table 4.4: Power rating of televisions as a function of their technology

TV technology	Power rating of televisions			
	Energy efficient TV		Non energy efficient TV	
	P_{ON}	P_{STBY}	P_{ON}	P_{STBY}
CRT	[70-110]	[4-10]	[70-110]	[4-10]
Plasma	[170-275]	[0,3-0,8]	[275-380]	[0,3-0,8]
LCD	[25-60]	[0,1-0,3]	[60-90]	[0,2-1]

The probability that a household possesses an energy-efficient appliance is denoted by $P(EAP)$. It is computed by using equation 4.2, which was presented earlier in chapter 3. The results for the two household examples are thus presented in Table 4.5.

$$P(EAP) = P(EAP | AG_{RP}, I_{HH}, EAL_{HH}) \quad (4.2)$$

Note that the environmental awareness level of a household, denoted by EAL_{HH} , is calculated as shown earlier in section 3.3.1 of chapter 3.

Table 4.5: Appliance possession results for the two household examples

	Household 1	Household 2
Household type	Single-parent family	Couples without children
Reference person	Adult 1	Adult 1
$P(EAP/AG_{RP})$	0,6	0,7
$P(EAP/I_{HH})$	0,5	0,7
$P(EAP/EAL_{HH})$	0,36	0,64
$P(EAP)$	0,46	0,57

During a simulation, a random number R_3 is generated uniformly to determine whether the appliance is energy-efficient or not. Another random variable R_4 is generated for determining appliance's technology. The process which was detailed in the previous chapter is summarized in Figure 4.2.

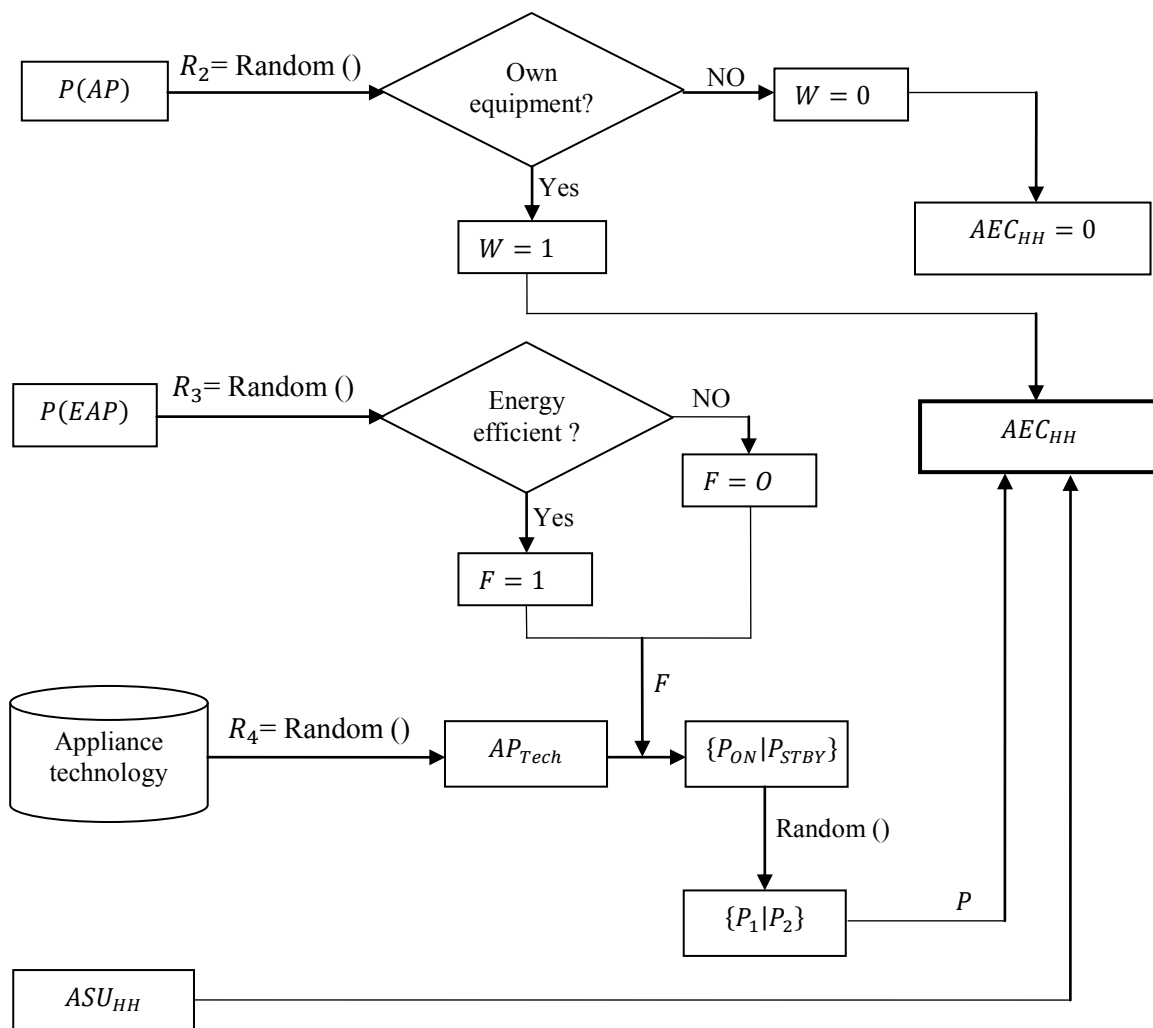


Figure 4.2 : Simulation process for calculating energy consumption of an activity

Using the values of W and F , we determine the power rating interval $\{P_{ON}|P_{STBY}\}$ of the appliance from Table 4.4. Then from this interval, random values for power rating are extracted, where P_1 is the power for ON mode and P_2 is the power for standby mode.

4.2.4 Service unit of activity “Watching TV”

4.2.4.1 Defining the service unit ASU

The service unit of the activity “watching TV” is defined to be the duration of watching TV in minutes per day. We consider the mean watching duration for each individual as a function of his/her age and socio-professional class (INSEE, 2012). In order to estimate the total service unit for a household, an aggregation of these individual service units is done.

4.2.4.2 Individual activity service units

The statistical data obtained from (INSEE, 2012) give mean TV watching durations as a function of the age and the socio-professional category of an individual. These data are presented in Table 4.6 and Table 4.7 respectively. As can be noticed from Table 4.6, watching duration of TV increases with the increase of age. Moreover, according to Table 4.7, this duration can vary among individuals as a function of the socio-professional class.

Table 4.6: Mean TV watching duration as a function of age (INSEE, 2012)

Age range	TV watching duration (min/day)
less than 14	120
15 à 19	129
20 à 29	151
30 à 39	152
40 à 49	161
50 à 59	172
60 à 69	217
More than 70	250

Table 4.7: Mean TV watching duration as a function of socio-professional class (INSEE, 2012)

Socio-professional class	TV watching duration (min/day)
Independent	135
Senior managerial staff	114
Middle level professions	140
Clerical and service staff	169
Manual workers	181

Consequently, the service unit for “watching TV” activity per individual is deduced from above table as a function of individual’s age and socio-professional class.

4.2.4.3 Household’s aggregate service unit

Watching TV in general is an activity which can be shared by members of the same family. Hence, in order to determine the total service unit of a household, sharing must be taken into account. A statistical data conducted by INSEE provides sharing coefficients of “TV watching duration” for French households according to their type (Table 4.8). This coefficient represents the percentage of time an individual watches TV with other members of his/her family from his/her total watching duration. For instance, a member belonging to a “couple without children” household spends 26% of time watching television alone. This means that for 74% of his/her time, he/she will be sharing the activity with one or more members of the family.

Table 4.8: Sharing and non-sharing coefficients for the ‘watching TV’ activity as a function of household type

Household type	Sharing coefficient per individual (S)	Non-sharing time coefficient
Single person	0	1
One-parent family	0,51	0,49
Couples without children	0,74	0,26
Couples with children	0,71	0,29
Others	0,57	0,43

The sharing process of “watching TV” activity can be given as shown in Figure 4.3 where ASU_1 , ASU_2 , and ASU_3 represent activity’s service units (watching TV) for three different household members. The household’s service unit, denoted by ASU_{HH} , can thus be estimated by aggregating these three individual service units. We do this by considering the least service unit (ASU_1 in this example) as reference value. We denote by S the sharing coefficient per individual (taken from Table 4.8). The sharing amount shared by all individuals will thus be equal to $[S \times (\min_i ASU_i)]$. Hence, the remaining time watched by each individual alone will be equal to $[ASU_i - S \times (\min_i ASU_i)]$. Consequently, the aggregated service unit ASU_{HH} of a household for the “watching TV” activity can be given as shown in equation 4.3.

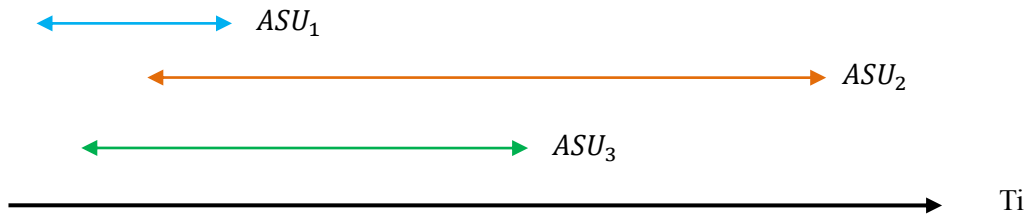


Figure 4.3 : Representation of the sharing process of “watching TV” activity

$$ASU_{HH} = \sum_{i=1}^{i=NO} ASU_i - \left[S \times (\min_i ASU_i) \times NO \right] + \left[S \times (\min_i ASU_i) \right] \quad (4.3)$$

Which can thus be written as:

$$ASU_{HH} = \sum_{i=1}^{i=NO} ASU_i - \left[(S \times (\min_i ASU_i)) \times (NO + 1) \right]$$

ASU_{HH} is the activity service unit of the household, where ASU_i is the activity service unit per individual, NO the number of occupants, and S is the sharing coefficient taken from Table 4.8.

We highlight here that in reality, sharing TV among individuals may be much more complex than what is represented here. For instance, each individual can share different durations with different family members. However, we do not think that this complexity is essential to be taken into account here, and that the simplified relation in equation 4.3 gives a very good representation of the sharing process among household members.

The sharing service unit ASU_{HH} calculated above is the one which is going to be used for estimating the energy consumption yielded by the “watching TV” activity. Yet, in order to have a better representation of occupants behavior towards watching TV at home, we introduce here two other scenarios other than the sharing one. These are the best case and worst case scenario, which are explained hereafter.

- **Best case scenario:** household members share the activity watching TV all the time (Figure 4.4). This scenario will thus represent the minimum consumption of energy.

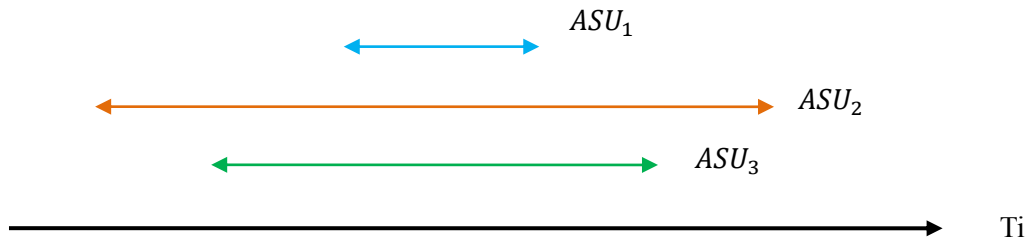


Figure 4.4 : Representation of the best case scenario for “watching TV” activity

For this scenario, the formula for calculating the aggregated service unit ASU_{HH} of a given household for the “watching TV” activity is given in equation 4.4.

$$ASU_{HH} = \text{Max} (ASU_i) \quad (4.4)$$

- **Worst case scenario:** household members do not share the activity at all. In this case activity sharing is equal to zero (Figure 4.5). This scenario will thus represent the maximum consumption of energy.

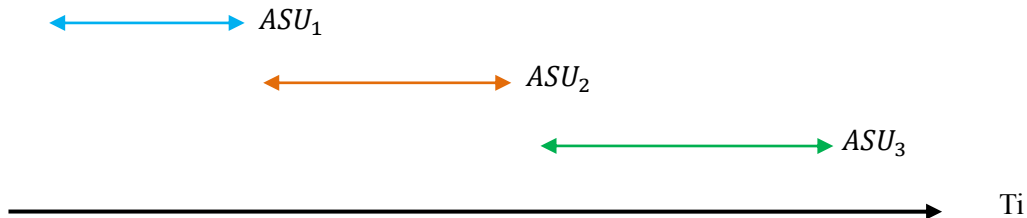


Figure 4.5 : Representation of worst case scenario for “watching TV” activity

For the worst case scenario, calculating the aggregated service unit ASU_{HH} of a given household for “watching TV” activity is given in equation 4.5.

$$ASU_{HH} = \sum_{i=1}^{i=NO} ASU_i \quad (4.5)$$

4.2.5 Calculating energy consumption

The energy consumption of activity “watching TV” is calculated according to equation 4.6, where AEC_{TV} represents the overall energy consumption of the activity TV for a given

household, AEC_{ON_TV} the consumption of the TV when switched on and AEC_{STBY_TV} the consumption of standby mode.

$$AEC_{TV} = AEC_{ON_TV} + AEC_{STBY_TV} \quad (4.6)$$

Where :

$$AEC_{ON_TV} = W \times F \times P_1 \times ASU_{HH}$$

$$AEC_{STBY_TV} = W \times F \times P_2 \times (24h - ASU_{HH})$$

Where W represents the possession of the TV appliance (1 if possessed and 0 if not), F represents the energy-efficiency of the appliance (1 if energy efficient and 0 if not), P_1 and P_2 represent the power consumed by the appliance when switched on and in standby mode respectively. ASU_{HH} is the aggregated service unit of the activity.

Hence, for each simulation, the model will yield three energy consumption values (AEC_{TV}) each corresponding to one of the three scenarios defined for the activity's service unit (ASU_{HH}).

4.2.6 Running simulations

Given the probabilistic nature of our model, **Monte Carlo technique** is used for running simulations. For each simulation run, different combination of variables is resulted and thus different consumption values. The number of iterations depends on the convergence of the results.

4.3 Testing model functionalities through simulation examples

For testing the functionality of the model as well as the validity of the results obtained, we perform a number of simulation examples for the three use-cases of the model. These use cases are described in the following.

4.3.1 Use case 1: simulating energy consumption for a specific household

First of all, the model can be used to quantify the energy consumption of a given activity (here “watching TV”) for a **given specific household** taken as input. The calculation is done

according to the simulation steps explained earlier. The simulation process for this use case is presented in Figure 4.6.

A specific household is defined manually by the user at the entry of the model. The different attributes such as household type, income, age and gender of individuals are defined at this step. Then simulations are generated with Monte Carlo method according to the simulation flow described in the previous section. The model will run for a number “ n ” of iterations till the convergence of the results. For each simulation run, three energy consumption values will be given at the model output corresponding to the three consumption scenarios defined earlier. For all of the n iterations, the results are represented with cumulative distribution plots as shown later.

In order to run simulation examples for this use case, we consider five different manually configured households and we perform the calculations for each one of them. The households are defined below. Simulation results are presented and discussed in the next section.

4.3.1.1 Household examples considered

- **Household 1:** Single person, male, aged 32, active employed, senior profession, with a long-term education level and an income of 2700 Euros/month.
- **Household 2:** Couple without children. Adult 1 is a male aged 37, active employed, senior profession, with long-term educational level and an income of 3000 Euros/month. Adult 2 is a female aged 34 years old, active and employed, middle level professions, with short-term higher education and income of 2300 Euros/month.
- **Household 3:** Couple with 3 children. Adult 1 is a male aged 45, active employed, clerical and service-staff profession, with a baccalaureate level education and an income of 2000 Euros/month. Adult 2 is a 40 years old female, non-active housewife, with a baccalaureate level education and no salary. The first child is a 9 years old girl, whereas the second and third are boys of 14 and 6 years old respectively. All children go to school.
- **Household 4:** One-parent family with one child. The parent is a 34 years old female, active employed in a middle level profession, with a short-term education level and an income of 1400 Euros/month. The child is a 5 year old boy who goes to school.
- **Household 5:** A couple of retired persons without children. Adult 1 is 66 years old male, inactive retired, short-term higher education level, and an income of 1300

Euros/month. Adult 2 is a 62 years old female, inactive retired, baccalaureate education level, and without income.

4.3.2 Use case 2: Randomly chosen household type with constraints

For the second use case, the model can be used to quantify energy consumption of a given activity (here “watching TV”) for a **random household** taken at the input. The advantage here is that while generating this random household, we can give some **constraints** on its attributes (Figure 4.7). This is an important feature which enables testing variability between households having one or more criteria (attributes) in common. For example, we can take randomly households of “couples without children” type, but put constraints on the income level for example. For instance, we can compare consumption values between two households having all attributes in common except for the environmental awareness level.

This feature is essential for assessing consumption variability between two or more households, and for assessing sensitivity analysis on model variables.

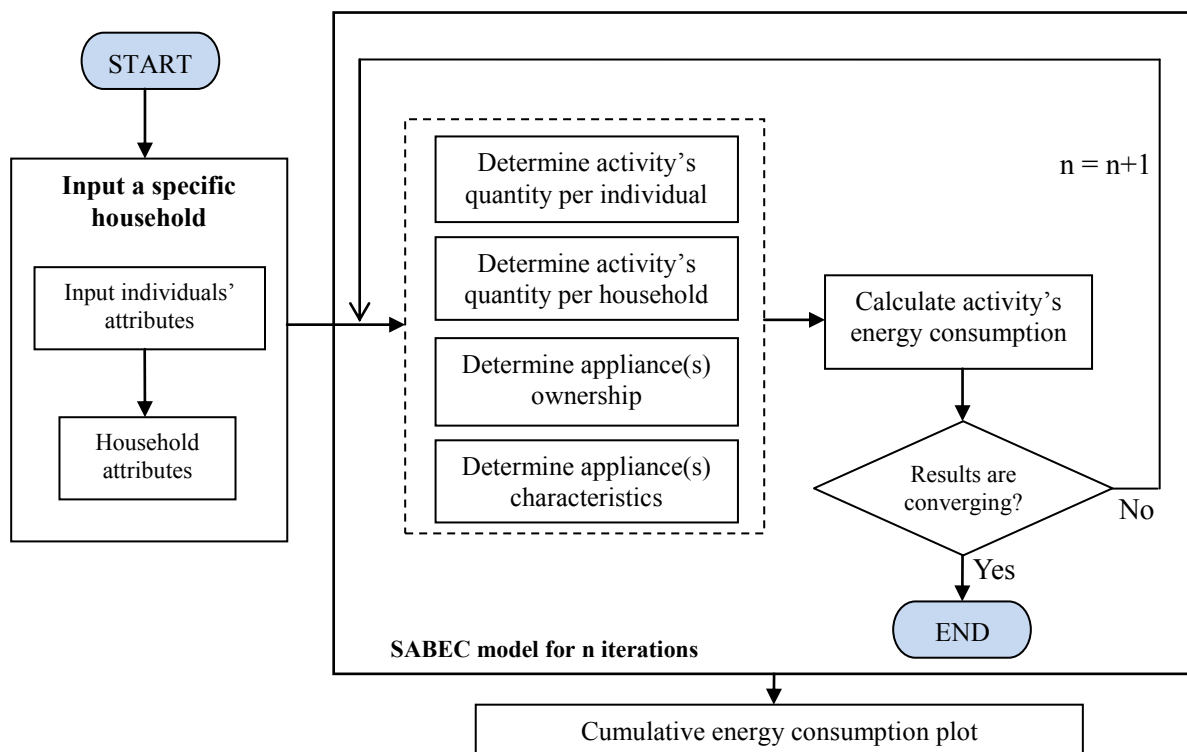


Figure 4.6 : Simulation process of SABEC model for use case 1

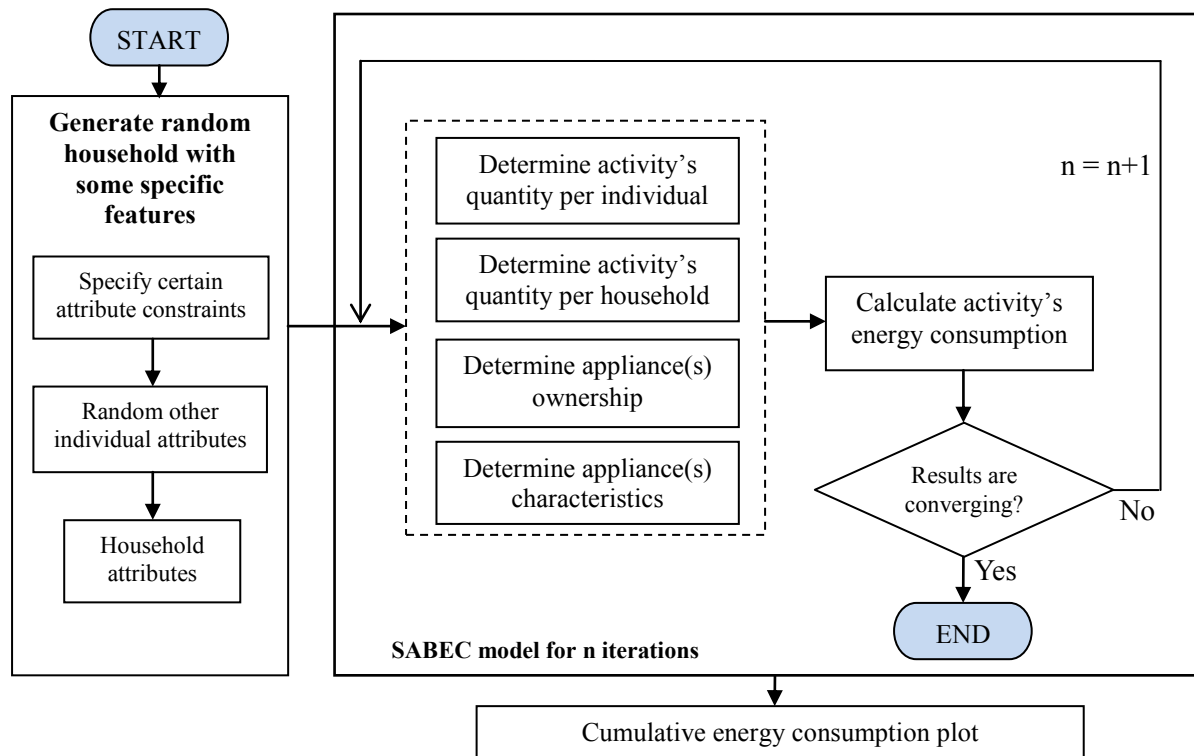


Figure 4.7 : Simulation process of SABEC model for use case 2

4.3.3 Use case 3: Randomly chosen population of households

For this third use-case (third functionality of the model), a population of households can be generated randomly by the model (

Figure 4.8). The model is capable of generating these randomly chosen households in coherence with the real population distribution. By this we mean that each random attribute generated respects the real features of the French population (taken from national statistics). For example, generating an education level of an individual is done as a function of his/her age. For instance, we cannot have a 16 years old individual with “higher-studies education level. As another example, generating a socio-professional class is done as a function of individual’s age and education level. The model filters incoherent cases such as an individual of age 28 having “retired” as employment status.

The energy consumption resulting from this third use-case can thus be representative of the total French population. Hence, simulation results can be compared to national studies on energy consumption, which is a crucial step for validating the model.

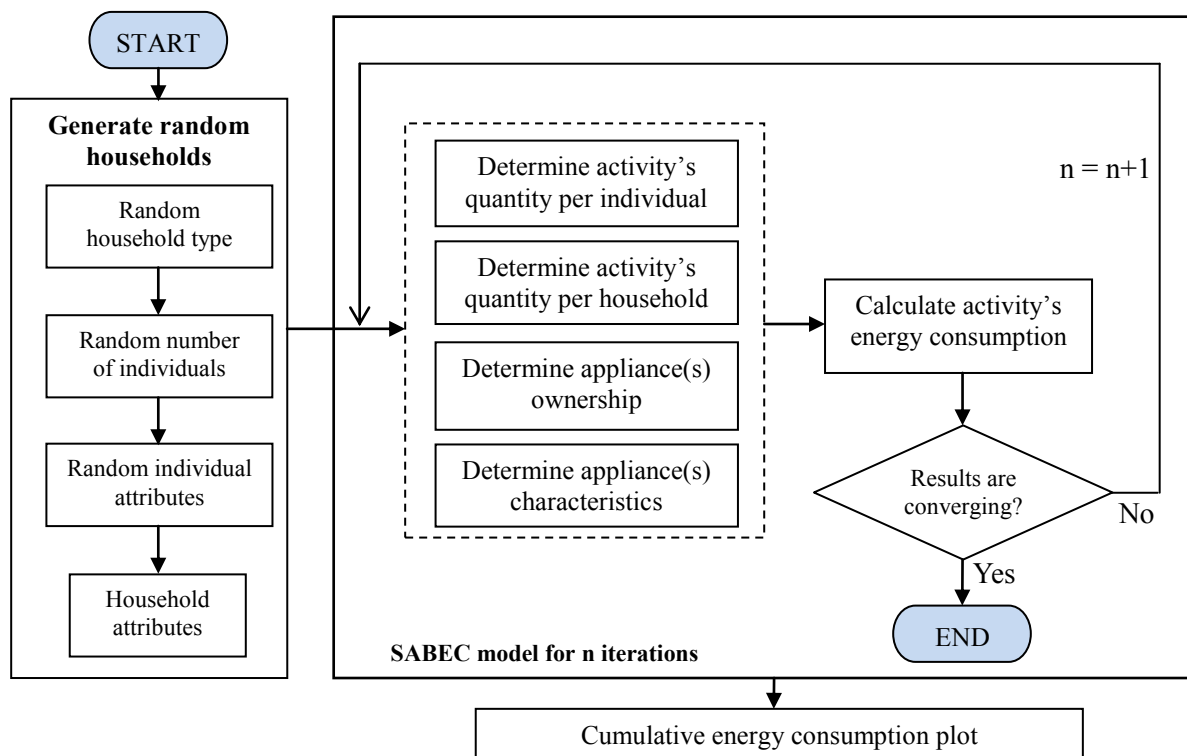


Figure 4.8 : Simulation process of SABEC model for use case 3

4.4 Results and discussions

A number of simulations are performed according to the three use-cases defined in the previous section. The results describing energy consumption for the activity “watching TV” are presented in the following.

4.4.1.1 Results for use-case 1

The attributes for the five households given in previous section are entered into the model and energy consumption is calculated for each of them. A number of 10000 simulations are performed for each household. First, the results of intermediary probabilities and activity service units are summarized in Table 4.9.

Second, mean energy consumption values (from 10000 simulation runs) are calculated for the five households. For each household, energy consumption values are given for the three scenarios: best case, worst case, and sharing case scenario (Table 4.10). Simulation results for each household are represented through increasing cumulative graphs as shown in Figure 4.9.

Table 4.9: Results of intermediary probabilities and parameters (use case 1)

	$P(AP)$	$P(EAP)$	Sharing coefficient (s)	ASU_{HH}		
				Best	Worst	Sharing
Household 1	0.846	0.823	0	114	114	114
Household 2	0.957	0.859	0.74	140	254	169
Household 3	0.990	0.859	0.71	169	690	349
Household 4	0.970	0.387	0.51	140	260	198
Household 5	0.998	0.268	0.74	217	434	273

Table 4.10: Mean energy consumption values for each household (use case 1)

	EC_{TV} (KWh/week)		
	Best	Worst	Sharing
Household 1	1.815	1.815	1.815
Household 2	2.399	4.057	2.830
Household 3	2.995	11.055	5.783
Household 4	2.690	4.671	3.661
Household 5	4.201	8.022	5.194

As can be concluded from Table 4.10 and Figure 4.9, household 1 which is a single person, shows the lowest energy consumption values among the five households. The plot for household 1 is showing a single line because all three scenarios are confounding since no sharing can take place. For all households, worst scenario values are the highest, which is normal because this is the case of highest service unit. The minimum value which is equal to zero corresponds to the case where the household do not possess a TV device. The maximum consumption values among households are coming from household 3 which is a couple and three children. This high value can be directly attributed to the higher number of occupants (5 occupants) than in other households. For a clearer comparison of energy consumption results for the five different households, we represent them through box plots as shown in Figure 4.10.

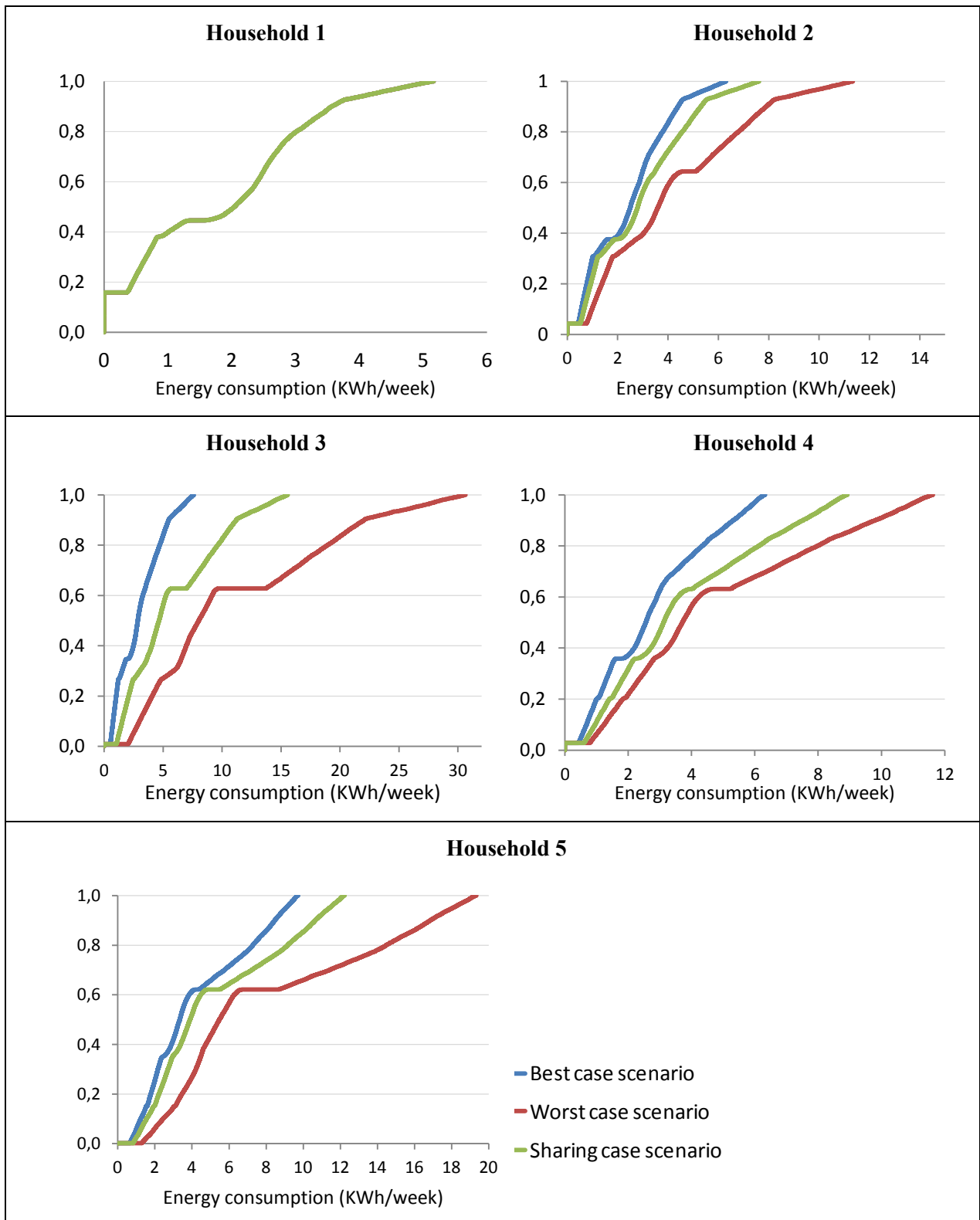


Figure 4.9: Cumulative distribution of energy consumption for the five households resulting from 10000 simulations (use case 1)

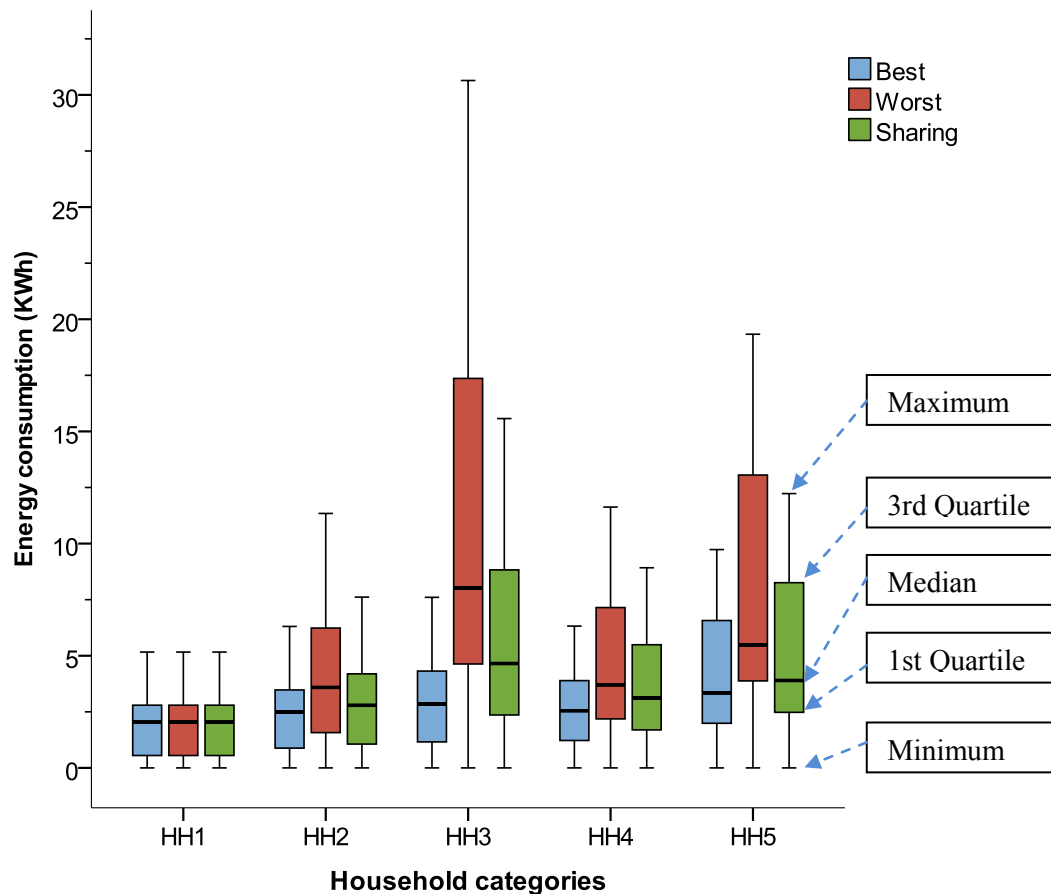


Figure 4.10: Simulation results for the five households (use case 1)

For the sharing scenario (in green), the median consumption values for households 1 through 5 are respectively 2.038, 2.787, 4.653, 3.114, and 3.896 KWh/week (Figure 4.10). Household 3 reveals the highest consumption values, while household 5 comes in the second place. This can be explained by the high TV watching durations of retired people living in household 3. Household 4 with a one-parent family and one child consumes energy for watching TV more than household 2 with a couple and no children. This can be attributed to two reasons. First the presence of children on household 4 increases watching duration since they watch TV more than active/working people. Second, the sharing coefficient of the TV watching activity is lower for one-parent family types (0.71) than couples family types (0.51). Thus, lower activity sharing yields to higher energy consumption values.

4.4.1.2 Results for use-case 2

For this use case, we consider two different examples. In both of them, random households are taken at the model input, where constraints can be defined on their attributes.

4.4.1.2.1 Example 1

In this example, we perform simulations by giving a constraint on the household type (Single, couples with children, couples without children, one-parent families). For each household type, we perform 10000 simulations. For each simulation, the model randomizes the attributes of each individual and then calculates the energy consumption of the activity ‘watching TV’ per household. Here also, the model outputs three consumption values corresponding to the three scenarios: Best, worst and sharing.

The details of simulation results are presented in Table 4.11. Consumption values are given by their mean (μ), minimum (m), maximum (M), median (χ), and standard deviation (σ) for each household and each scenario.

Table 4.11: Simulation results of energy consumption for “watching TV” activity (use case 2-example 1)

		Household type			
		Single	One-parent family	Couples without children	Couples with children
Number of simulation runs		10000	10000	10000	10000
Best case scenario (KWh/household/week)	m	0	0	0	0
	M	8.96	8.29	9.92	8.05
	μ	3.04	3.01	3.32	2.97
	σ	2.08	1.92	2.15	1.87
	χ	2.75	2.77	3.02	2.89
Worst case scenario (KWh/household/week)	m	0	0	0	0
	M	8.96	19.12	18.10	27.01
	μ	3.04	6.09	5.84	8.58
	σ	2.08	4.34	4.02	6.00
	χ	2.75	4.59	4.71	6.72
Sharing case scenario (KWh/household/week)	m	0	0	0	0
	M	8.96	13.82	12.06	14.65
	μ	3.04	4.63	4.00	4.98
	σ	2.08	3.19	2.66	3.36
	χ	2.75	3.68	3.43	4.27

The minimum value which is equal to zero corresponds to the case where the household does not possess a TV. For the sharing case scenario, mean consumption values indicate that

couples with children have the highest consumption levels with 4.98 KWh/week, followed by one-parent families with 4.63 KWh/week, couples without children with 4.0 KWh/week, and finally singles with 3.04 KWh/week.

For a clearer comparison between the five households, we present simulation results of energy consumption through the box plot in Figure 4.10 and Figure 4.11. Some outliers may arise in simulation results; however their occurrence is minimal and thus is not considered in the plot. From the box-plot, median energy consumption values reveal that couples with children are the highest consumers with 50% of consumption values lying above 4.27 KWh/week for the sharing scenario (Figure 4.11). One-parent families come in the second place with 50 % of consumption values lying above 3.68 KWh/week. The third place is for couples without children with 50 % of consumption values lying above 3.43 KWh/week. The lowest consumers are singles with 50 % of consumption values lying above 2.75 KWh/week

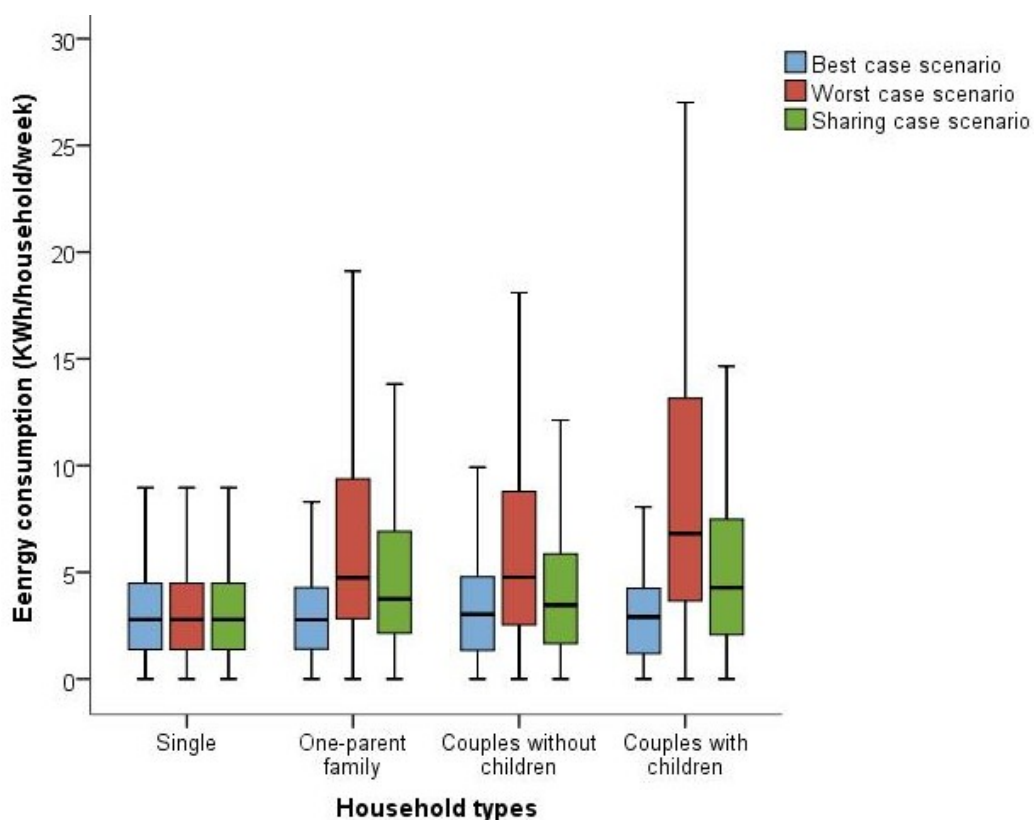


Figure 4.11 : Simulation results of energy consumption for “watching TV” activity (use case 2-example 1)

4.4.1.2.2 Example 2

In this example, we go further in details and we use the model to calculate energy consumption values for a **homogenous sample**. We consider here only households of “couples with children” type and we define constraints on the number of children. Thus the aim is to analyze consumption variation as a function of the number of children per household. We take the three cases as shown in Table 4.12.

Table 4.12: Number of children considered for simulating energy consumption for “watching TV” activity (use case 2-example 2)

Case	1	2	3
Number of children	[1,2]	[3,4]	[5,6]

For each case, 10000 simulation runs are performed. For each simulation, the model randomizes the attributes of each individual and then calculates the energy consumption of the activity ‘watching TV’ per household. Here also, the model outputs three consumption values corresponding to the three scenarios: best, worst and sharing. Simulation results are summarized through a box plot in Figure 4.12.

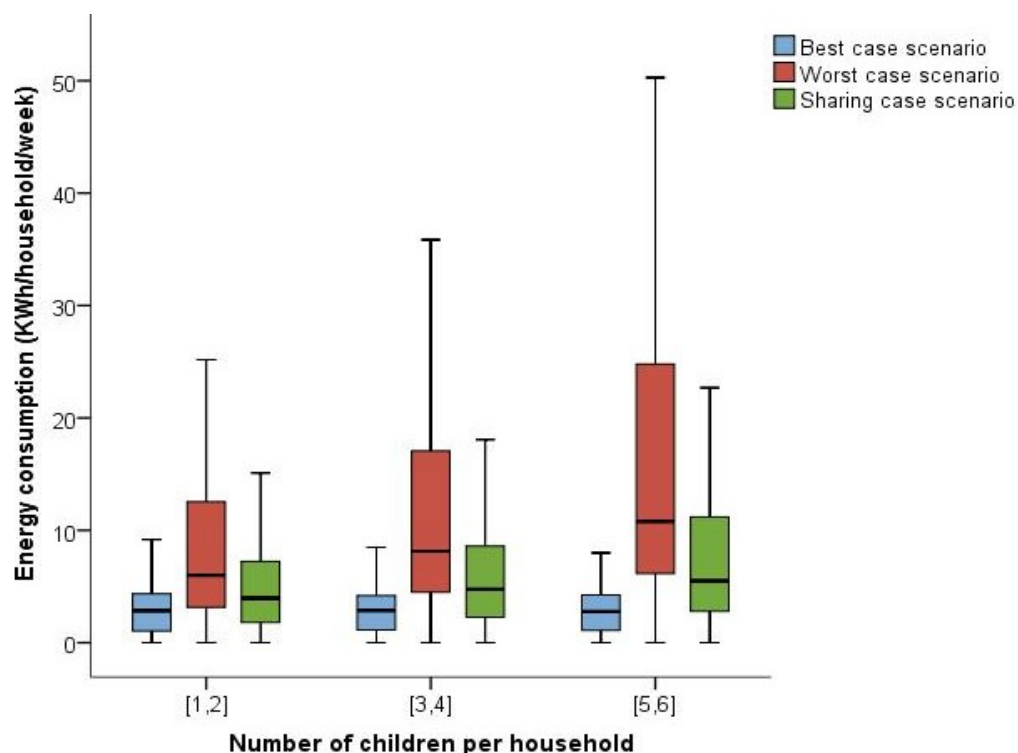


Figure 4.12 : Simulation results of energy consumption for “watching TV” activity (use case 2-example 2)

From Figure 4.12, it can be noticed instantly that energy consumption varies directly with the number of children per household. The higher the number of children, the higher is the energy consumption for the activity ‘watching TV’. In households comprising five to six children, consumption can attain a maximum value of 22.68 KWh/week for the sharing scenario, while it does not exceed 15 KWh/week for households with one to two children, and 18.06 KWh/week for households with three to four children.

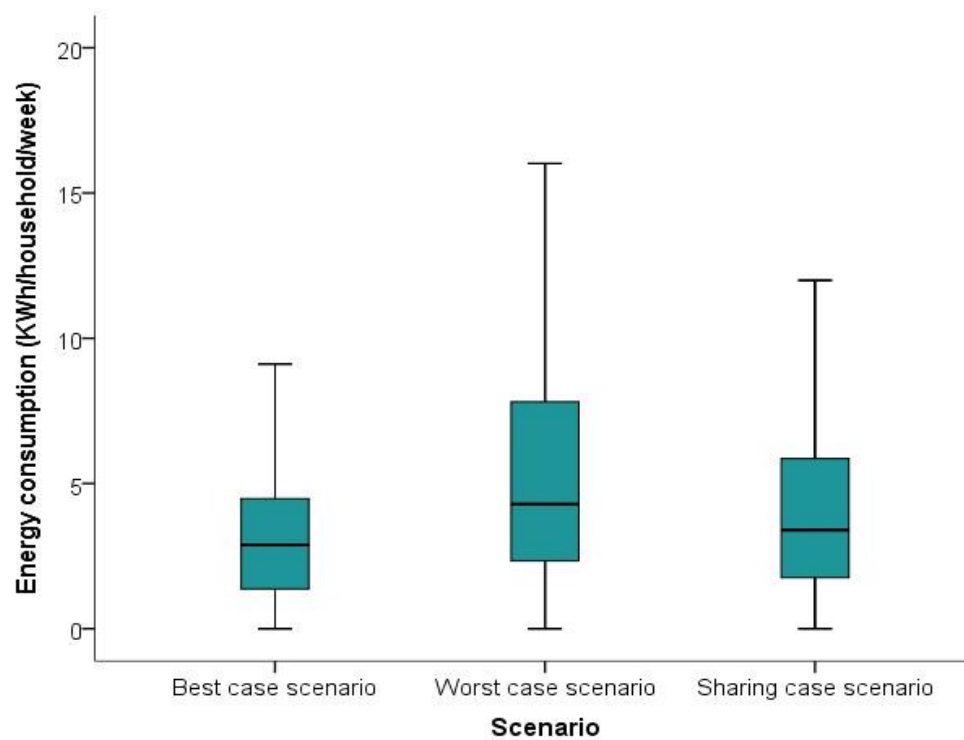
4.4.1.3 Results for use-case 3

For this use case, ten thousands households are generated randomly according to population distributions (as discussed in section 4.3.3). The corresponding energy consumption for activity ‘watching TV’ is calculated for each of these households. Simulation results for the three scenarios (best, worst and shared) are summarized in Table 4.13.

For the sharing case scenario, the mean consumption value is 3.95 KWh/household/week with a standard deviation of 2.76 KWh/week. The median of the distribution is equal to 3.33 KWh/week. The range of consumption between minimum and maximum values is equal to 11.99 KWh/week. The average consumptions for both best and worst case scenarios are 3.09 KWh/week and 5.01 KWh/week respectively. The box plot of energy consumption simulation results is presented in Figure 4.13.

Table 4.13: Simulation results for use case 3

		Mean energy consumption for 10000 randomly chosen households
Best case scenario (KWh/household/week)	m	0
	M	9.11
	μ	3.09
	σ	2.03
	χ	2.84
Worst case scenario KWh/household/week)	m	0
	M	16.02
	μ	5.01
	σ	3.72
	χ	4.02
Sharing case scenario KWh/household/week)	m	0
	M	11.99
	μ	3.95
	σ	2.76
	χ	3.33

**Figure 4.13 :** Simulation results for use case 3

4.5 Model validation

In order to validate the model proposed in this chapter, we compare its simulation results of energy consumption for activity ‘watching TV’ against real measured data. The real data in our possession comes from a study conducted by a French company (ENERTECH) in the scope of an European project called REMODECE (Enertech, 2008). This study measures electricity consumption of television devices in 99 French households. The households considered in the mentioned study are chosen arbitrary without any constraints on their demographic or socio-economic attributes. The resulting consumption values from the measurement study are presented in Figure 4.14 in an ascending order. The minimum consumption witnessed among the 99 monitored households is 0.3 KWh/week and the maximum is 21.03 KWh/week, while the mean is 5.65 KWh/week (Enertech, 2008).

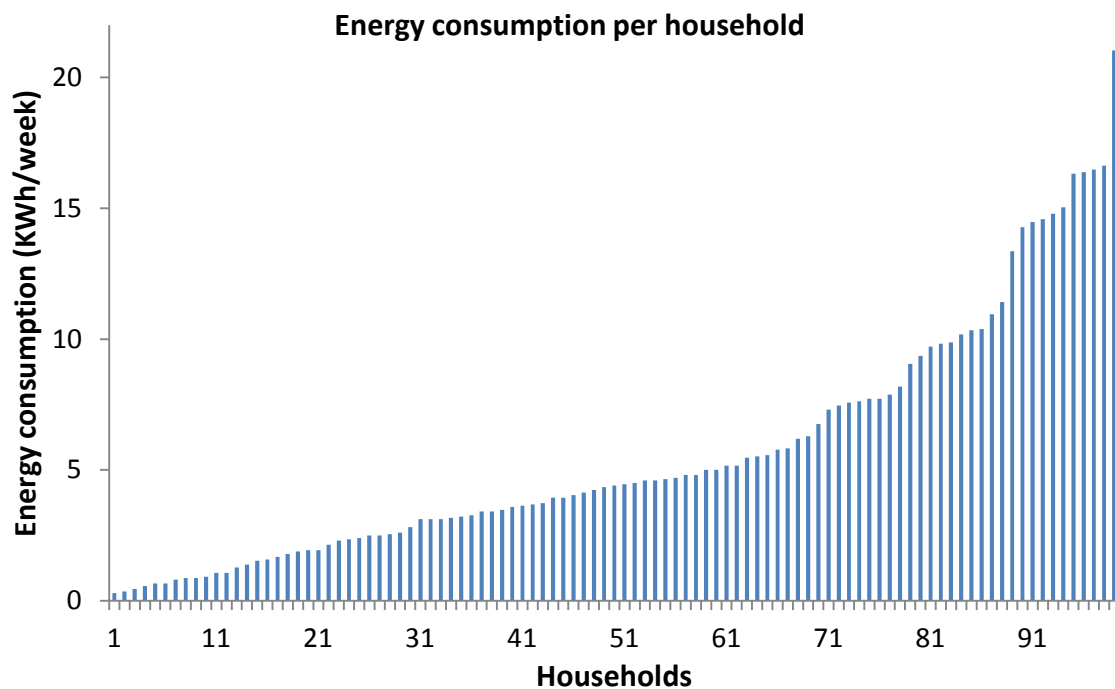


Figure 4.14 : Energy consumption of televisions per household [monitored data from (Enertech, 2008)]

In order to compare our model’s simulation results to the real data, we follow the procedure presented in Figure 4.15. First, we perform population-wise simulations according use-case 3 explained earlier in section 4.3.3. Energy consumption simulations for the activity ‘watching TV’ are performed for 10,000 randomly chosen households. Here we consider only results for the “sharing-case scenario”. Then, from these ten thousand households, we draw arbitrarily a

sample of 99 households (same number as the real data sample). Zero simulation values are not considered since they correspond to households without TV's (This is because real measured data comes only from households owning televisions). Simulation results yielded by SABEC model for the 99 randomly chosen households are shown in Figure 4.16.

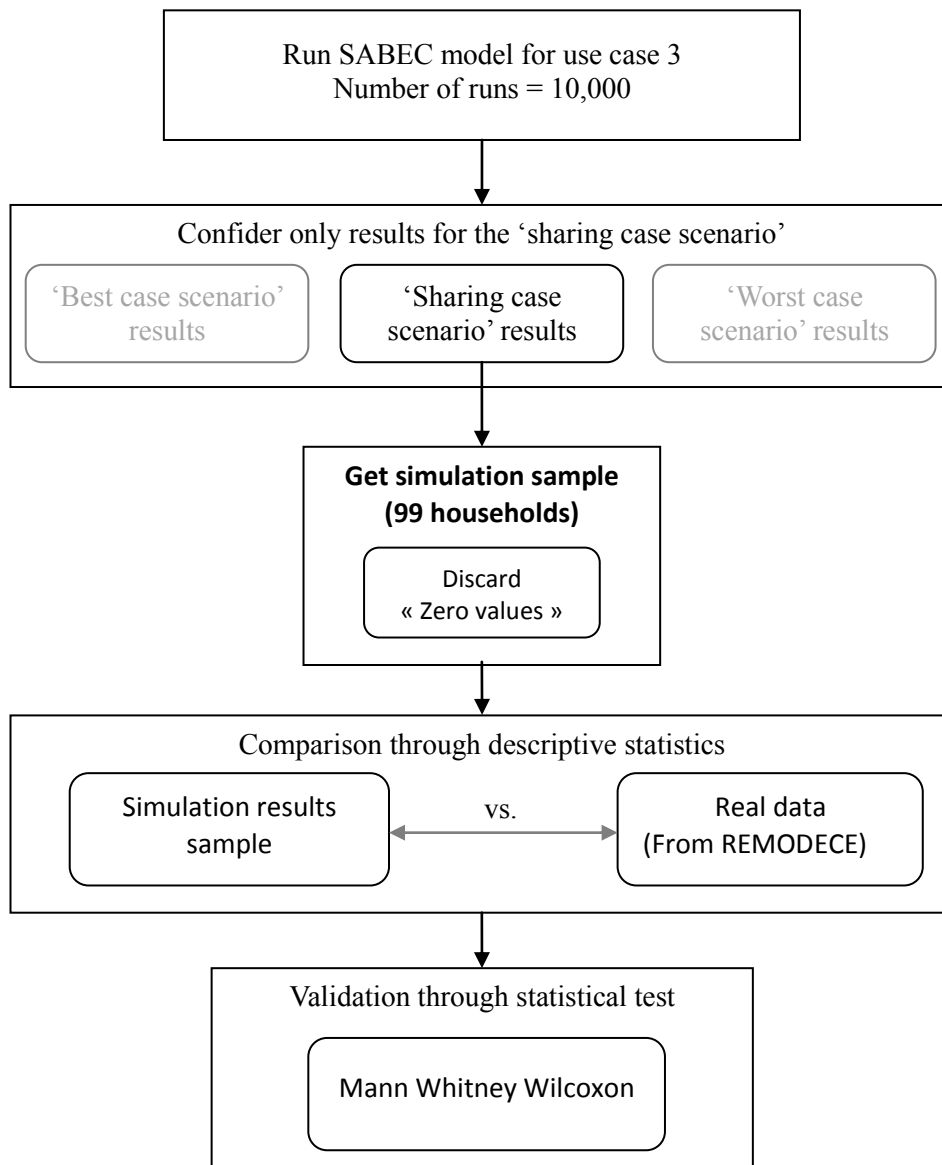


Figure 4.15 : Model validation procedure

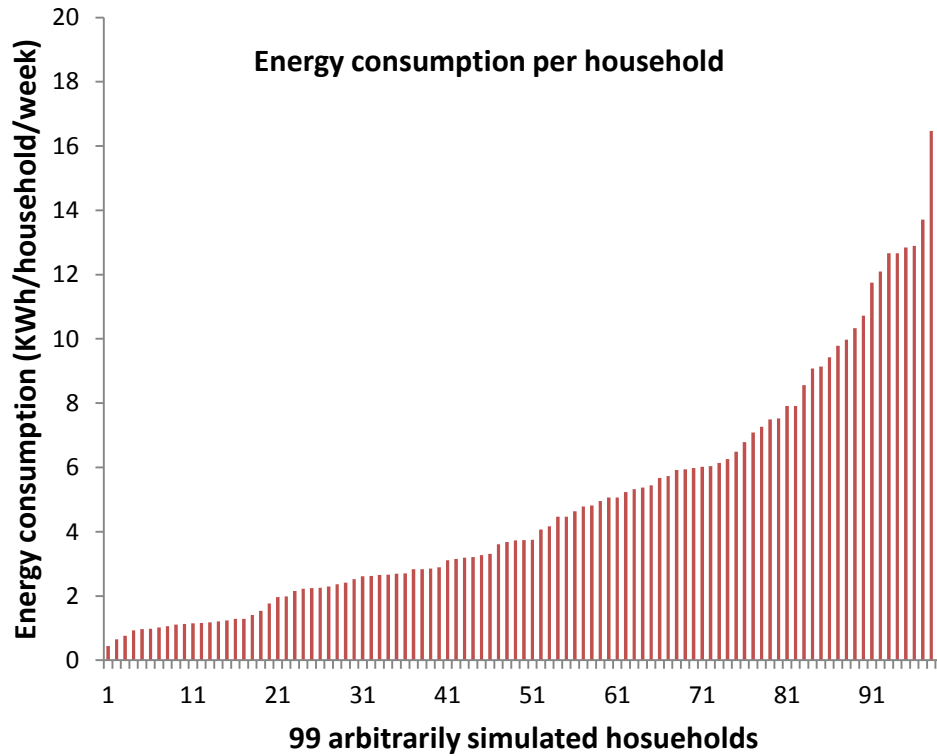


Figure 4.16 : Energy consumption of « watching TV” activity per household (SABEC simulation results)

4.5.1 Validation through descriptive statistics

A first comparison between energy consumption distributions from both simulation results and real data is performed through their corresponding descriptive statistics as shown in Table 4.14. At first glance, the mean values (μ) of both distributions seem to be close to each other with $\mu = 4.956$ KWh/week for simulation results and $\mu = 5.653$ KWh/week for real monitored data.

Table 4.14: Comparing simulation results to real data through their descriptive statistics

	Simulation results (sharing case scenario)	Real data from (Enertech, 2008)
m	0.45	0.30
M	18.64	21.03
μ	4.956	5.652
σ	3.807	4.547
χ	3.74	4.40

The maximum consumption value for the real data ($M = 21.03$) is higher than that of simulation results ($M = 18.64$), while the minimum value is lower. This comparison is better seen through the box plot for both distributions as shown in Figure 4.17. The points represented by small circles above the box plots represent outliers. According to the box plot, the respective median values (χ) of real and simulation data are 4.4 and 3.74 KWh/household/week. These values are not very far from each other, revealing thus little difference between model results and real measured consumption values.

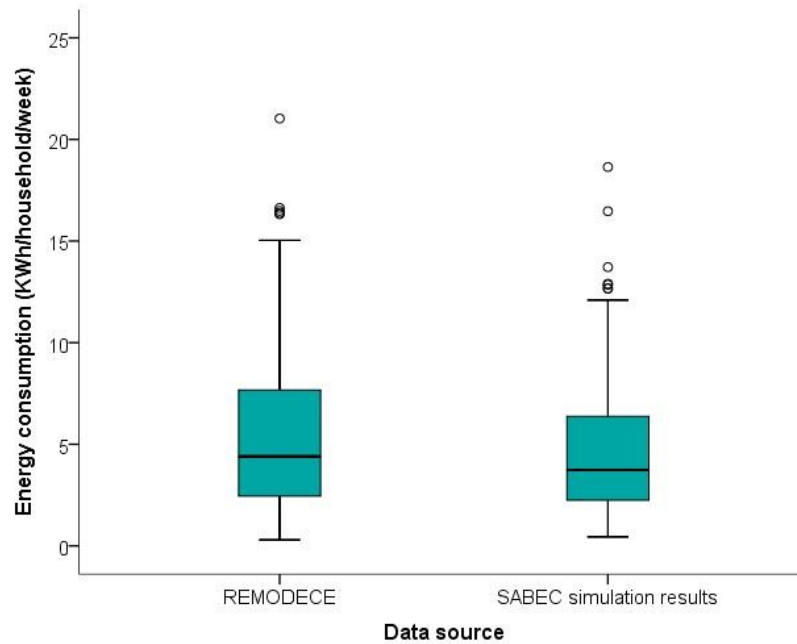


Figure 4.17 : Comparison between simulation results and real data

4.5.2 Validation through statistical test

In order to compare simulation results yielded from the model and real measured data taken from the study, a non-parametric statistical test is performed. We have chosen to compare both samples through a Mann–Whitney–Wilcoxon test which is a commonly used method especially for the case of independent and non-normal distributions. The test is performed using the SPSS statistical analysis software. We run the test with a 95% confidence interval. Test results are summarized in the Table 4.15.

Table 4.15: Mann–Whitney- Wilcoxon test results

Null hypothesis	Test	Significance (p-value)	Decision
The distribution is the same across both samples	Mann–Whitney- Wilcoxon test	0.427	Retain null hypothesis

The p-value resulting from this non-parametric test is equal to 0.427. For Mann–Whitney-Wilcoxon test, this p-value indicates that the null hypothesis can be retained, meaning that both samples have the same distribution.

The results from this statistical test, coupled with descriptive statistics comparison carried out above, both confirm the similarity of energy consumption distributions for activity ‘watching TV’ between simulation results and real data. These results give a clear validation of SABEC simulation model for “watching TV” activity.

4.6 Conclusions

In this chapter, we applied the proposed stochastic activity-based energy consumption model (SABEC) on activity “watching TV”. First, a description of this activity is given and the reasons of choosing it as a case study are exposed. Modeling steps for activity ‘watching TV’ according to SABEC model are then presented. The choice of model variables and the statistical data used as well as their nature and sources are presented and discussed. The quantification logic of activity’s service unit is demonstrated through three different scenarios: worst, best and sharing. Simulation examples are then performed through the three different functionalities of the model: (1) for specific households, (2) for random households with constraints on attributes, and (3) for random population-wise households. For each of these three cases, simulation results are used to assess and interpret energy consumption variation between households in function of their attributes. Energy consumption variability between different households is assessed through a number of examples. Finally, the model is validated by testing the statistical significance of its simulation results against real measured data. This is done through descriptive statistics and a non-parametric statistical test.

Chapter 5: Application of SABEC model for the “washing laundry” activity

In this chapter, we apply the proposed SABEC model on the domestic activity “washing laundry”. First, a description of the activity is given and its different facets are discussed. The modeling logic is then presented and the main variables that influence energy consumption in this activity are exposed. Details on the statistical data being considered, their nature and sources are presented and discussed. Then we demonstrate how the SABEC model can be applied to model and simulate energy and water consumption yielded by the considered activity. Similarly to the “Watching TV” activity in chapter 3, a number of simulation examples are undertaken in order to test the model’s functionalities. Simulation results are used to interpret the variation in energy consumption among different households. Finally, we validate the proposed model by testing the statistical significance of simulation results against real consumption data on a population-wide scale.

Due to the lack in French statistical data concerning laundry habits, we conducted a web-based survey to track the trends of “washing laundry” within French households. 105 respondents from different household types participated in the survey. The results provide us with a comprehensive knowledge base on cloth washing habits in French residential buildings. Some of the statistical data collected from the survey is used to improve the representativity of the model. The web-survey conducted along with its results is presented in appendix A.

5.1 Introduction

Doing laundry at home is one of the major domestic activities since people wash their dirty laundry on a regular basis. The washing machine is a commonly used device and an integral part of most households all over the world. Almost 95% of French households possess washing machines in their dwelling (INSEE, 2010). This high ownership rate is accompanied with an extensive use of washing machines and thus high levels of energy and water consumption. In average, a washing machine consumes 169 kWh/year per French household (SIDLER, 2009), where this value represents about 7% of French households' total electricity consumption (ADEME, 2012b). A life cycle assessment of washing machines conducted by Bourrier et al. concludes that 80% of machine's environmental impacts are yielded during the use phase (Bourrier et al., 2011). This conclusion indicates that the effect of a washing machine on the environment relies heavily on consumers' behavior.

The habits related to laundry washing can vary significantly from one household to another. Different families produce different quantities of dirty laundry, and may use a different number of washing cycles and temperature settings. According to a nation-wide study conducted by ENERTECH, the number of washing cycles among French households varies from 1 to 16 cycles per week (Enertech et al., 2008). This variation in washing trends results in large variations in energy and water consumption. For instance, energy consumption of washing machines per household may reach 850 kWh/an, which is five times higher than the average value of 169 kWh/year (Enertech et al., 2008). In addition, the diversity in washing machine models available in the market today is another reason of this variation.

Given these facts, the activity "washing laundry" is chosen to be our second case study for applying the SABEC model. The most important aspects that differentiate this activity from the one considered in chapter 4 (Watching TV) are: (1) First, in this activity both electricity and water flows are considered, (2) more complex activity patterns (Higher number of variables, more divergent energy consumption behaviors), and (3) a more complex method for quantifying the service unit of the activity.

In this chapter, we first present a description of the activity "washing laundry" where we discuss its different facets. The modeling logic is then presented and the main variables considered are exposed. After that, we demonstrate how the SABEC model can be applied to model and simulate energy and water consumption yielded by the subject activity. Simulation

examples are then performed on a number of household examples, and their results are discussed. Finally, simulation results are compared to real data for the validation of the model.

5.2 Description of “Washing laundry” activity

Doing laundry is the process by which households clean their laundry at home. Laundry materials are composed of both clothes worn by individuals in addition to house linens⁶. The laundry process at home, which we denote as “Aggregate laundry” (in chapter 2), encompasses a number of operations as shown in Figure 5.1. It comprises using (wearing clothes, using towels and bed sheets, etc.), sorting (separating dirty laundry in distinct baskets to be washed separately), washing (cleaning laundry by machine or hands), drying (on a clothes drying rack, by a tumble dryer, etc.), and ironing of laundry. The first two steps (i.e. using and sorting) represent people’s behavior towards using and cleaning laundry, and they are the key elements for quantifying energy flows of the laundry process.

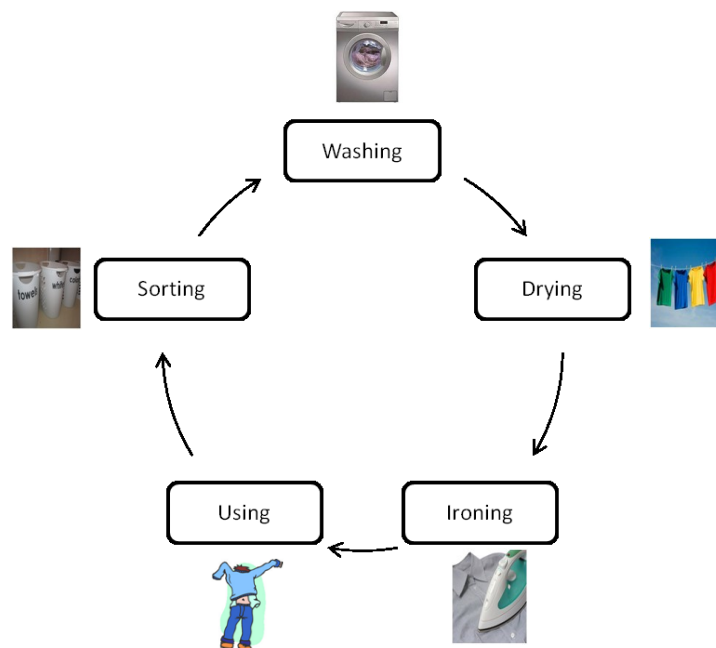


Figure 5.1: Representation of the aggregate “Laundry” activity

As exposed in chapter two, we split up the “aggregate laundry” activity into three distinct and dependant activities: Washing laundry, drying laundry and ironing laundry. In this chapter, we deal only with the activity “washing laundry” which is described hereafter.

⁶ Linens are fabric household goods intended for daily use, such as bedding, table cloths and towels

5.2.1 Main trends of the activity “washing laundry”

People use washing machines in order to wash their accumulated quantity of dirty laundry. The quantity of dirty laundry yielded by a household is directly related to their habits of using (wearing clothes, using linens) and changing of laundry. In addition, the patterns by which households sort their laundry for washing has a direct impact on the number of washing loads and thus on washing machine’s energy and water consumption. Therefore, we consider the “washing laundry” activity through three different steps: using, sorting and washing, as shown in Figure 5.2. The description of these steps is further detailed below.

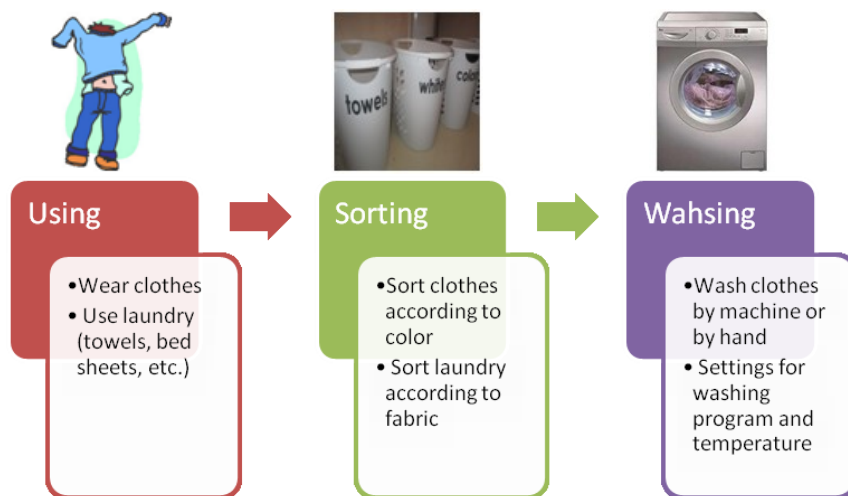


Figure 5.2 : Representation of the activity “washing laundry”

5.2.1.1 Using Laundry

5.2.1.1.1 Using clothes

Each individual wears a quantity of clothes per day. The mean weight of clothes dressed by a French adult per day is about 1.2 Kg. This value is calculated according to data taken from a French web survey as shown in Table 5.1 (Tout Pratique, 2013).

The quantity of clothes dressed per day can vary from one person to another according to some factors such as the body volume, gender, profession, etc. In our model, we consider this quantity to be proportional to ones’ body volume which is in turn a function of age. The quantification of activity’s service unit will be discussed in details in section 5.3.3

Table 5.1: Mean weight of clothes per French adult per day (Tout Pratique, 2013)

	Weight per article (in grams)	Mean weight dressed per adult per day (in grams)
Adult jeans	1000	750
Adult cotton pants	500	
Shirt or blouse	200	187.5
T-shirt	150	
Light dress	150	
Sweat-shirt	250	
Socks	20	20
Underwear	100	100
pajamas	250	250
Total		1237.5

5.2.1.1.2 Using linens

Home linens are also used by households on a daily basis. Linens are fabric household goods intended for daily use, such as bedding, table cloths and towels. Their quantity, size, color, and type of fabric can differ from one household to another. However, we simplify here by only considering a general quantity of linens per household. The data giving the list of linens and their corresponding weight are taken from a survey found on the web (Tout Pratique, 2013). We attribute number of articles as a function of household type so that to get the total weight of linens per household (Table 5.2). The quantity of laundry yielded by a household per month is directly related to their frequency of changing.

5.2.1.1.3 Changing rate

The changing rate represents the frequency by which an individual puts his clothes into dirty laundry baskets in order to be washed. In reality, this rate may vary from one person to another according to his/her age, gender, working status, or even his/her socio-professional class. However, no statistical data is available to establish a correlation between the changing rate and these attributes.

The conducted survey gives an insight about changing rates for different laundry types (Appendix A). Survey results reveal that the changing rate of clothes is influenced by individuals' age (adults, children). The different frequencies and their probability distribution resulting from the survey are given in Table 5.3. For instance, the majority of children (69%)

changes clothes on a daily basis. As for adults, changing clothes once every two days is the most common trend (43%).

Even though people may change certain clothes with different frequencies (for example, shirts and under-wears are changed more frequently than jeans), however, here we simplify by considering that individuals change all of the clothes they are wearing on a day. This simplification may yield energy consumption values slightly higher than reality, yet this is analyzed further in simulation results. The only attribute retained in the model for determining an individual's changing rate of clothes is his/her respective age. Other attributes are not considered due to lack of statistical data. Home linens are changed less frequently than clothes. In general, their changing frequency is once or twice per month for each household.

Table 5.2: Total weight of linens per household (Tout Pratique, 2013)

	Weight per article (g)	Number of articles per household			
		Single	One-parent family	Couples without children	Couples with children
Bed sheet 1 place	450	2	2	0	2
Bed sheet 2 places	800	0	2	1	2
Quilt Cover	1500	1	4	2	4
Pillow slip	200	2	4	3	4
Table cloth	250	1	2	1	2
Dish cloth	100	2	2	2	2
Large bathrobe	1500	1	1	1	2
Small bathrobe	1200	0	1	2	1
Large towel	700	2	3	3	3
Small towel	300	2	2	2	2
Total weight per household type (QL_{HH})		6750	15400	11450	16900

Table 5.3: Probability distribution of 'clothes changing rate' per individual (from survey)

	Changing rate value	Probability distribution	
		Children	Adults
Every day	1	69 %	33 %
Once every two days	2	23 %	43 %
Once every three days	3	8 %	24 %
		100 %	100 %

The total quantity of clothes used (dressed and changed) by household individuals per month, added to the used quantity of linens, constitutes thus the service unit of the activity “washing laundry” (in Kg). The calculation of this service unit is further detailed in section 5.3.3.

5.2.1.2 Sorting

Several studies reveal that people sort their dirty laundry before washing (Enertech et al., 2008; Roberts, 2012). The survey we conducted reveals that 86% of households declare sorting their laundry so that to be washed separately and at different temperatures (Table 5.4).

Table 5.4: Probability distribution of sorting of laundry per household (from survey)

Laundry sorting	Percentage of households
Yes	86 %
No	14 %

Laundry is mainly sorted into clothes and linens as shown in Figure 5.3. According to survey results, 80% of respondents declare that laundry’s color is their main determinant for sorting it. They sort clothes into dark and light colored (Light = light-colored and white clothes). Some households declare sorting laundry as a function of fabric type and dirtiness, yet this is done rarely and these factors are thus not taken into account in our model.

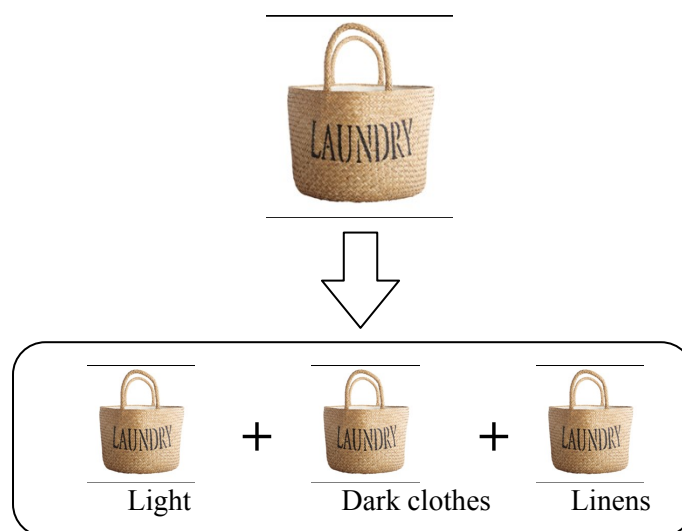


Figure 5.3 : Laundry sorting

The ratio of light clothes (light colored and white clothes) to the total quantity of clothes varies from one household to another. According to results from the survey, the percentage of

light-colored clothes ranges from 10 % to 60 %. The different proportions (of light clothes over the total) and their probability distribution are presented in Table 5.5. For instance, 28 % of surveyed households declare that light clothes represent 30 % of their total laundry.

Table 5.5: Distribution of light-colored clothes proportion of the total laundry (From survey)

Percentage of light-colored clothes over the total	Probability distribution
10%	11%
20%	26%
30%	28%
40%	18%
50%	10%
60%	7%
Total	100 %

The sorting of laundry induces thus different washing temperatures. Relations between laundry type and washing temperature settings are discussed in the following section.

5.2.1.3 Washing

Households wash their laundry according to the way the latter is used and sorted as described previously. The two main parameters of washing laundry are the washing temperature and the filling ratio of machine's drum.

5.2.1.3.1 *Washing temperature*

When people sort their laundry, they do this in the purpose of washing it at different temperatures. Elevated washing temperatures consume more energy than lower temperatures. This is due to the fact that almost 80% of energy consumption per cycle is used for heating water to attain the desired temperature (ADEME, 2010). According to some studies, a cycle at 30 °C consumes three times less energy than a cycle at 90 °C (Bosch, 2013; Eneritech et al., 2008). Such studies reveal also that people choose washing temperatures mainly as a function of their clothes color (white, light-colored and dark-colored). Moreover, temperatures used for washing linens are often different from those used for washing clothes. The same findings are also drawn from our web survey.

- **In case of sorting (86%)**

Different washing temperatures, revealed from survey, for washing light-colored clothes, dark-colored clothes and lines are presented in Table 5.6 together with their corresponding probability distributions.

Table 5.6: Washing temperatures and their probability distribution (sorting-case)

Washing temperature	Probability distribution for light-colored clothes	Probability distribution for dark-colored clothes	Probability distribution for linens
30 °C	26%	48%	13%
40 °C	44%	44%	30%
60 °C	24%	8%	52%
90 °C	6%	0 %	5%
Total	100 %	100 %	100 %

From Table 5.6, we notice that high temperature levels are used mainly for light-colored clothes and linens. Dark-colored clothes are often washed at 30 °C or 40 °C (92%). Only 6% of households declare washing their light-colored clothes at 90 °C.

- **In case of no-sorting (14%)**

When households do not sort their laundry, this means that they use the same washing temperature for all types and colors of laundry. The washing temperatures collected from the survey for this case are shown in Table 5.7 with their corresponding probability distributions. In this mixing (no-sorting) case, relatively low temperatures are used. People declare using low temperatures so that to avoid damaging their clothes' colors.

Table 5.7: Washing temperatures and their probability distribution (no-sorting case)

Washing temperature	Probability distribution
30 °C	47%
40 °C	40%
60 °C	13%
90 °C	0%
Total	100 %

5.2.1.3.2 Filling ratio

The filling ratio is defined as the quantity of laundry that people fill into machine's drum, divided by the machine's nominal capacity. Different households have different filling ratios ranging in general between 50% and 100% (Enertech et al., 2008).

The filling ratio has a direct influence on the number of washing cycles per household, and thus on energy and water consumption. Different filling ratios results from our survey are presented in Table 5.8 together with their probability distribution. From this distribution, we notice that the majority of households (43%) declare filling their washing machine drums at a ratio of 90% each time they load a cycle.

Table 5.8: Probability distribution of filling ratio (from survey)

Filling ratio of machines drum (<i>FR</i>)	Probability distribution
60%	6%
70%	4%
80%	24%
90%	43%
100%	23%
Total	100 %

The distribution of filling ratios in Table 5.8 will be used later on for the calculation of number of washing cycles, and thus for calculating energy consumption. We are here aware that people declarations may differ from reality but we did not investigate further as we should quickly get reference numbers to feed our simulation model.

5.2.2 Washing machine characteristics

A washing machine is characterized by a number of aspects that influence the way it is used and the energy it consumes. A washing machine can be characterized by its installation mode (free standing or built in), type (frontal or top), capacity (drum capacity in Kg), energy rating (energy class), water intake connection, water and electricity consumption per cycle, and washing programs.

In our model, we shall not consider all of these factors even though each of them can have an influence on the energy consumption related to the activity "washing laundry". The reason is that we are interested in modeling activity patterns due to occupants' attributes rather than

those due to appliance attributes. Hence, two main characteristics related to cloth washers' are considered in our model, which are the machine's **charging capacity** and the **energy rating** (Electricity and water consumption). These two attributes have direct influences on the use trends of washing machines as well as the activity patterns of households (number of cycles for example).

5.2.2.1 Washing machine's capacity

The capacity of a washing machine represents the maximum quantity of laundry that can be charged into machine's drum to be washed in a single cycle. According to washing machines manufacturers, the capacity can vary as a function of laundry's fabrics (Darty, 2013). The maximal capacity indicated on a machine corresponds to the quantity of cotton fabrics. This value is lower for other fabrics such as linen, synthetic or others. For instance, A washing machine with a capacity of 5 kg of cotton, can contain a load of only 2.5 kg of synthetic fabrics (Darty, 2013).

Due to the lack of statistical data about capacities of cloth washers present within French households, we use the results of the survey which we conducted. The different capacities and their distribution within French households (105 households) are given in Figure 5.4 and Table 5.9.

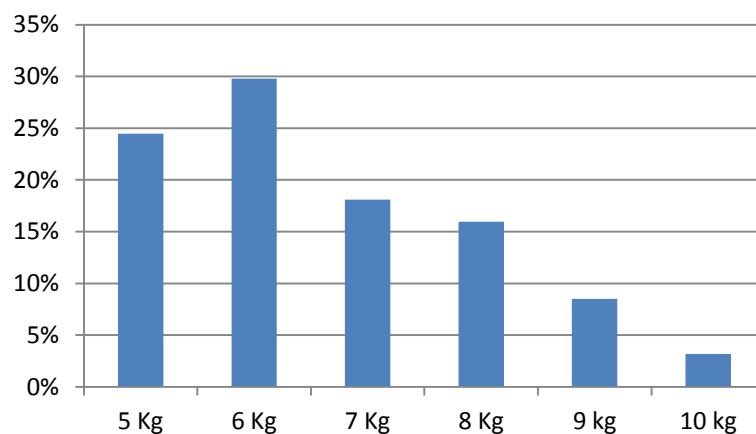


Figure 5.4 : Probability distribution of washing machine capacities (From survey results)

According to the results of the survey, no correlation exists between households' attributes and the capacity of their washing machine. Small households (ex. Single households) may own a washing machine of 8 Kg capacity, while large families (ex. couples with 3 children) may own a smaller washing machine of 5 or 6 Kg capacity.

Table 5.9: Probability distribution of washing machine capacities (from survey results)

Washing machine capacity (Kg)	Probability distribution
5	24 %
6	30 %
7	18 %
8	16 %
9	9 %
10	3 %
Total	100 %

5.2.2.2 Washing machine's energy rating

The energy rating of a washing machine represents its electricity and water consumption levels. European and French norms impose on manufacturers to display energy labels on each electro domestic device so that to inform consumers about its performance and power consumption (ECDGE, 2013). For washing machines, the European standard evaluates energy efficiency in terms of classes ranging from A+++ (most efficient) to G (least efficient). Energy class corresponds to energy consumption in kWh per kg of laundry for the standard cotton cycle at 60 °C, denoted by $P_{WM,60^{\circ}C}$ (Table 5.10). Devices labeled from A to A+++ are considered to be energy-efficient, while others are not.

The water consumption per cycle may vary as a function of machine's characteristics. According to a study of the inter-professional group of manufacturers of domestic appliances (GIFAM), recent energy-efficient washing machines consume two to three times less water than older non-efficient ones (GIFAM, 2012). The water consumption per kilogram of laundry is given in Table 5.10 (GIFAM, 2012; Picard, 2008). The power rating at 60°C is also given in KWh/kg with an interval of values.

As discussed earlier, energy consumption of a washing machine per cycle is influenced directly by the washing temperature. A number of energy consumption measurements campaigns reported linear relationships between washing machines' energy consumption and the different washing temperatures used (ADEME, 2010; Enertech et al., 2008). For instance, these studies conclude that a washing cycle at 30 °C consumes three times less energy than a cycle at 90 °C, and two times less than a cycle at 60°C. Therefore, taking the energy consumption at 60 °C (from Table 5.10) as a reference value, the energy consumption for the different temperatures is deduced as shown in Table 5.11.

Table 5.10: Energy labels, power rating and water consumption of washing machines (ECDGE, 2013; GIFAM, 2012)

	Energy label	Power rating at 60 °C , $P_{WM,60\text{ }^{\circ}\text{C}}$ (KWh/kg) [min, max]	Water consumption (Liter/kg)
Energy efficient	A+++	[0.11, 0.13]	7
	A++	[0.13, 0.15]	
	A+	[0.15, 0.17]	
	A	[0.17, 0.19]	
Not energy efficient	B	[0.19, 0.23]	20
	C	[0.23, 0.27]	
	D	[0.27, 0.31]	
	E	[0.31, 0.35]	
	F	[0.35, 0.39]	
	G	[0.39, 0.43]	

Table 5.11: Determining power rating at each washing temperature

	Coefficient	Power consumption (KWh/Kg)
For 30 °C	0.5	$P_{WM,30\text{ }^{\circ}\text{C}} = P_{WM,60\text{ }^{\circ}\text{C}} \times 0.5$
For 40 °C	0.66	$P_{WM,40\text{ }^{\circ}\text{C}} = P_{WM,60\text{ }^{\circ}\text{C}} \times 0.66$
For 60 °C	1	$P_{WM,60\text{ }^{\circ}\text{C}}$ (From Table 5.10)
For 90 °C	1.5	$P_{WM,90\text{ }^{\circ}\text{C}} = P_{WM,60\text{ }^{\circ}\text{C}} \times 1.5$

Having determined the energy and water consumption of a washing machine per Kg, the energy and water consumption per cycle can now be estimated by multiplying these values with the capacity of the machine.

5.2.3 Energy and water consumption

The energy and water consumption for the activity “washing laundry” depend directly on the use pattern of washing machines. The use pattern is represented globally by the frequency of washing (number of washing cycles) and the choice of washing temperatures (washing program).

The number of washing cycles per household is a function of the quantity of laundry produced by a household, the machine’s capacity, and the filling ratio of machine’s drum. These relations are represented in Figure 5.5 and illustrated by the following:

Electricity and water Consumption = fn(number of cycles, washing temperature)

Number of cycles = fn(Quantity of laundry per household, capacity, filling ratio)

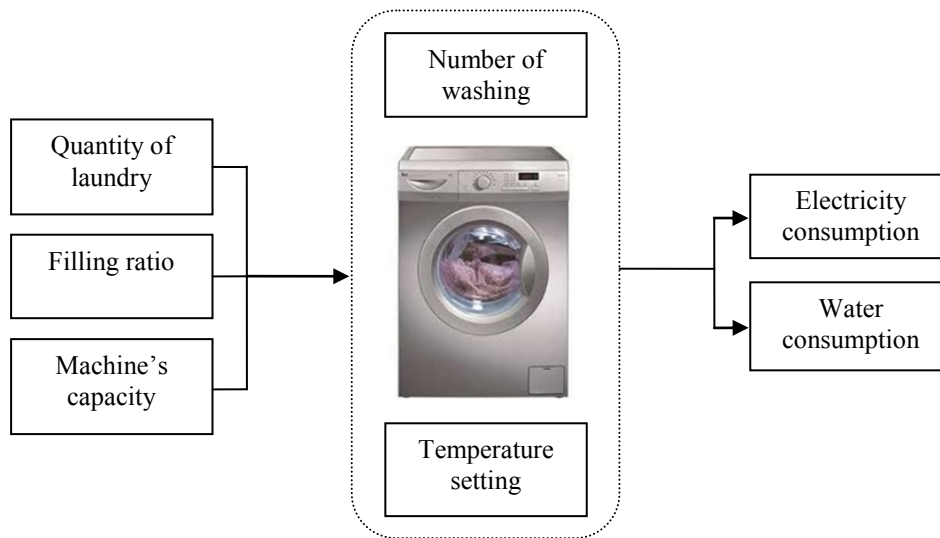


Figure 5.5 : Determining electricity and water consumption

5.3 Applying SABEC model to the activity “washing laundry”

5.3.1 Determining ownership rate of washing machines

For calculating ownership levels of appliances, national statistical data of ownership rates are used (INSEE, 2010) (refer to chapter 3, section 3.3.2). The probability that a household possesses a washing machine appliance is denoted by $P(AP)$. It is computed by using equation 5.1, which was detailed earlier in chapter 3 (section 3.2.1).

$$P(AP) = P(AP | HH_{type}, SPC_{HH}, AG_{RP}) \quad (5.1)$$

During a simulation, the ownership rate of a washing machine device for a given household is estimated stochastically through Monte Carlo technique. A random number R_2 is generated and compared to $P(AP)$ (refer to chapter 3, section 3.3.2.1).

5.3.2 Determining washing machine characteristics

As mentioned in the activity description in section 2.1, the two characteristics of washing machines considered in our model are the machine’s capacity and the energy rating.

5.3.2.1 Determine washing machine's energy rating

The probability that a household possesses an energy-efficient appliance is denoted by $P(EAP)$. It is computed by using equation 5.2, which is presented earlier in chapter 3 (section 3.2.).

$$P(EAP) = P(EAP | AG_{RP}, I_{HH}, EAL_{HH}) \quad (5.2)$$

During a simulation, the energy efficiency of a washing machine is determined stochastically through Monte Carlo technique. A random number R_3 is generated and compared to $P(EAP)$.

Once we know whether the appliance is efficient or not, we must determine its energy label so that to deduce its corresponding power rating. This is also done stochastically where a random number R_4 is generated and energy label⁷ (EL_{WM}) is drawn from Table 5.10 (Between A and A+++ classes for efficient, and between B and G classes for not efficient). The corresponding power rating of the machine for a cycle at 60 °C ($P_{WM,60\text{ }^\circ\text{C}}$) is thus deduced from Table 5.10. Power ratings for other temperature settings are deduced as shown earlier in Table 5.11.

5.3.2.2 Determining washing machine's capacity

We denote by C_{WM} the charging capacity of a washing machine. For a given household, C_{WM} is determined stochastically through Monte Carlo technique. The distribution of washing machine capacities already exposed in Table 5.9 is used. A random number (R_5) is generated and the capacity is deduced through the inverse of the cumulative distribution. The calculation logic is shown in Table 5.12.

Table 5.12: Random process for determining washing machines' capacity

Condition on the value of the random number R_5	Washing machine capacity (Kg)
$0 < R_5 \leq 0,24$	5
$0,24 < R_5 \leq 0,54$	6
$0,54 < R_5 \leq 0,72$	7
$0,72 < R_5 \leq 0,88$	8
$0,88 < R_5 \leq 0,97$	9
$0,97 < R_5 \leq 1$	10

⁷ We consider a uniform probability distribution for both efficient energy labels [$P(A) = P(A+) = P(A++) = P(A+++)$] and non-efficient energy labels [$P(B) = P(C) = P(D) = P(E) = P(F) = P(G)$].

In Figure 5.6, we summarize the modeling process for determining appliance ownership and characteristics. W represents the possession of an appliance determined through the random number R_2 , and F represents the energy efficiency of the appliance determined through the random number R_3 . EL_{WM} is the energy label of the washing machine and is determined through the random number R_4 . $P_{WM,60^\circ C}$ is the power rating of the machine for a cycle at $60^\circ C$, and \tilde{W} is the water consumption per cycle.

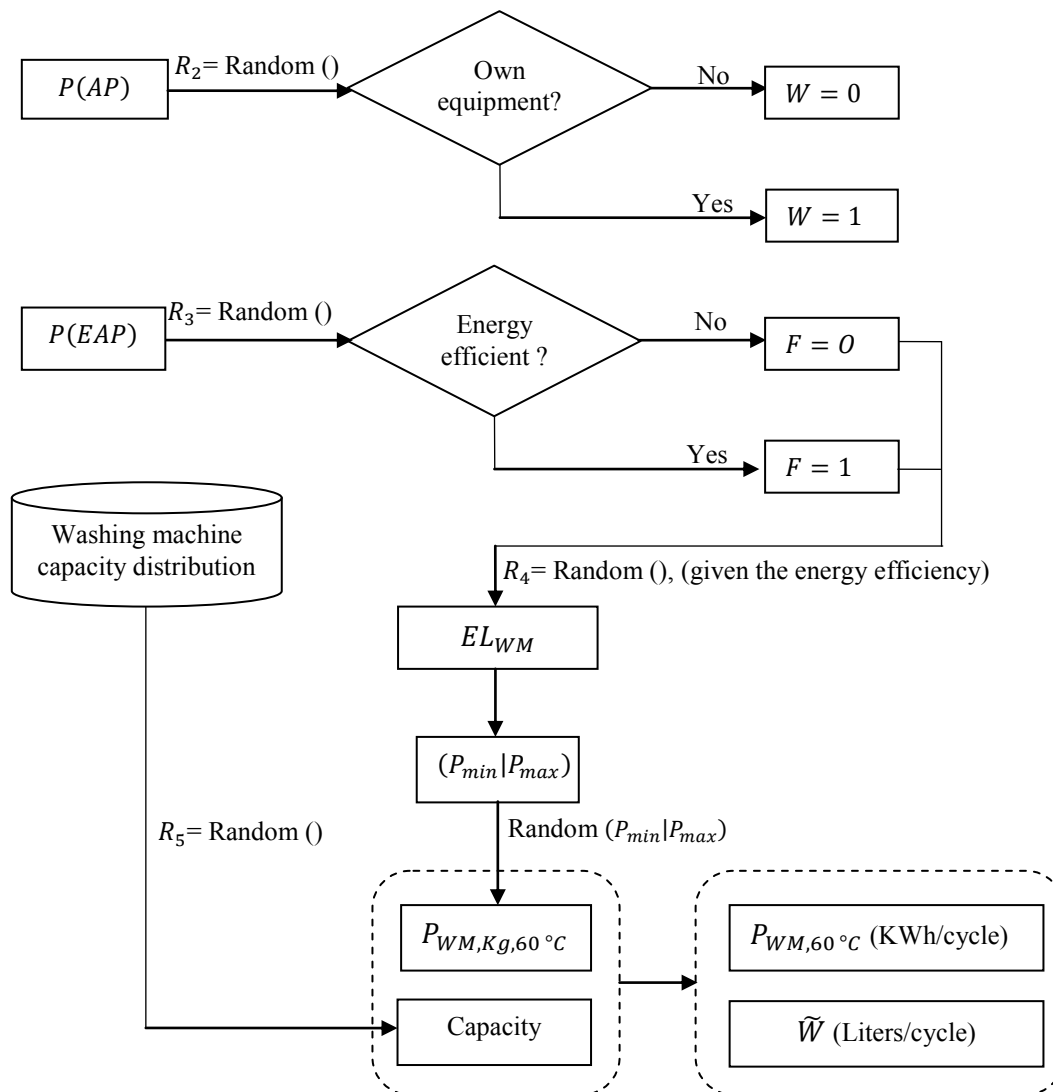


Figure 5.6 : Modeling process for determining appliance ownership and characteristics

5.3.3 Service unit of the activity “Washing laundry”

We define the service unit of the activity “Washing laundry” to be the quantity of dirty laundry (clothes and linens) produced by a household per month (in kilograms). The quantity

of ‘Laundry clothes’ is determined on an individual scale, while that of ‘Laundry linen’ is determined on the household scale. This is further explained in the section hereafter.

5.3.3.1 Quantity of clothes per individual

Each individual wears a given quantity of clothes per day. This quantity depends mainly on one’s body surface area. The body surface area is a function of human’s height and weight (Haycock et al., 1978), which are in turn correlated to age and gender. In a first approximation, it is thus possible to directly relate the weight of clothes dressed by an individual to his/her age and gender.

We are going to do this by relating the body surface area (and thus weight of daily clothes dressed) of any individual to that of a reference individual. The values of reference corresponding to an average French adult are shown in Table 5.13. The height and weight corresponding to an average French adult, denoted by \bar{H} and \bar{W} respectively, are taken from a national measurement campaign conducted by the French institute of textiles and clothing IFTH (IFTH, 2013). The mean weight of clothes dressed by a French adult per day, denoted by \overline{QC} , is taken from Table 5.1. The body surface area of an individual, denoted by BSA_i , is calculated according to Haycock formula given in equation 5.3, where W_i represents an individual’s weight in Kg and H_i his/her height in cm (Haycock et al., 1978).

$$BSA_i = 0.024265 \times W_i^{0.5378} \times H_i^{0.3964} \quad (5.3)$$

The formula of body surface area introduced by Haycock can be applied for weights ranging from 1 to 120 Kg, and heights ranging from 30 to 200 cm.

Table 5.13: Parameters related to average male and female French adults

Parameter	Symbol	Value	
		Male	Female
Body weight	\bar{W}	77.4 Kg	62.4 Kg
Body height	\bar{H}	175.6 cm	162.5 cm
Body surface area	\overline{BSA}	1.951 m ²	1.685 m ²
Mean weight of clothes dressed by a French adult per day	\overline{QC}	1.2 Kg	1.2 Kg

The BSA of a given individual can be estimated if we have his/her height and weight. These can be determined as a function of the age by using national French statistics. Tanguy et al.

confirm that the body weight of French individuals follows a normal distribution whose parameters depend essentially on age (Tanguy et al., 2007). Probability distributions of weight for both males and females according to their age categories are given in Appendix B. For example, male individuals of 16 years have a mean weight of 64.8 Kg with a standard deviation of 9.6 Kg (Appendix B). Thus, given the age of an individual, it is possible to estimate his/her weight based on the corresponding normal distribution.

In addition, the average height of an individual can be estimated given his/her age. We consider here the mean values similarly to those used in French body growth curves (GFA, 2013). These data are given in appendix B. We highlight here that mean values of height are used, and not probability distributions of height as a function of age, due to lack in statistical data.

We denote by QC_i^d the quantity of clothes dressed by an individual per day. According to what explained earlier, we determine a linear dependence between this quantity and the individual's body surface area. The formula is given in equation 5.4 and illustrated in Figure 5.7.

$$QC_i^d = (BSA_i \times \overline{QC}) / \overline{BSA} \quad (5.4)$$

Which can thus be written as

$$QC_i^d = 0.614 \times BSA_i \text{ for males}$$

$$QC_i^d = 0.711 \times BSA_i \text{ for females}$$

Where BSA_i is the body surface area of an individual and calculated according to equation 5.3.

To determine the quantity of dirty laundry per individual per month, the **changing rate** of clothes is needed. We denote by CR_i the clothes changing rate of clothes per individual. It is estimated randomly based on the data presented earlier in Table 5.3. Thus to estimate the changing rate for an individual (CR_i), a random variable R_6 is generated uniformly and the rate is estimated from the probability distribution in Table 5.3. This step is illustrated in Table 5.14.

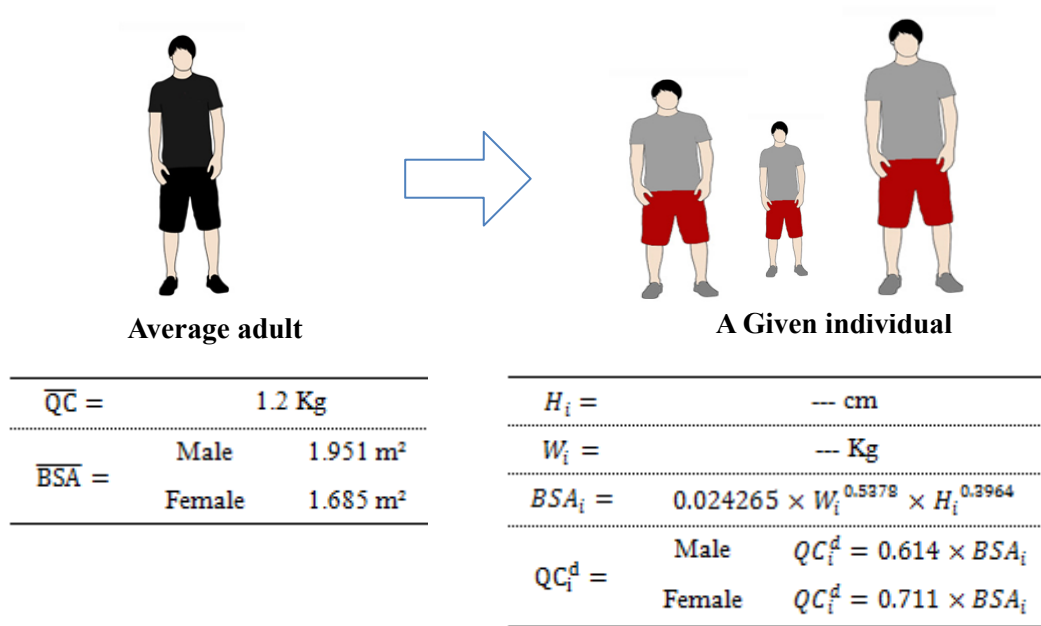


Figure 5.7 : Determining quantity of clothes dressed by an individual per day

Table 5.14: Determining clothes changing rate per individual (randomly)

	Condition of the random variable R_6	Clothes changing rate (CR_i)
For children	$0 < R_6 \leq 0.69$	1
	$0.69 < R_6 \leq 0.92$	2
	$0.92 < R_6 \leq 1$	3
For adults	$0 < R_6 \leq 0.33$	1
	$0.33 < R_6 \leq 0.76$	2
	$0.76 < R_6 \leq 1$	3

We denote by QC_i^m the quantity of dirty clothes (to be washed) produced by an individual per month. This quantity is calculated according to equation 5.5.

$$QC_i^m = QC_i^d \times (30/CR_i) \tag{5.5}$$

Where QC_i^d is the quantity of clothes dressed per day, and CR_i is the changing rate.

5.3.3.2 Quantity of clothes per household

According to the survey, people living in the same dwelling tend in most cases to wash their clothes together (same laundry baskets and same washing machine). Only few respondents

declared separating their dirty laundry from that of other cohabitants. About 90% of couples with children, one parent families, and even couples without children declare washing clothes together with other household members. This value is lower only for the case of room-mates (two or more adults not constituting a couple or a family), where 44% of respondents declared separating their laundry and thus their washing cycles from those of their room-mates.

We consider that the service unit of the activity “washing laundry” for a given household to be **additive**. This means that the total quantity of clothes laundry per household per month is equal to the sum of all individual quantities as shown in equation 5.6.

$$QC_{HH}^m = \sum_i^{NO} QC_i^m \quad (5.6)$$

Where NO is the number of household occupants and QC_i^m is the quantity of dirty clothes (to be washed) produced by an individual per month.

Sorting: As stated earlier, some households separate their clothes into light and dark colored. The percentage of light-colored clothes differs from one household to another. The survey yielded the proportions shown earlier in Table 5.5

We denote by q to be the percentage of light-colored clothes over the total quantity of clothes per household. During a simulation, q is estimated randomly from the distribution presented in Table 5.5. A random number R_7 is generated and q is estimated as shown in Table 5.15.

Table 5.15: Random process for determining proportion of light-colored clothes

Condition of the random variable R_7	Proportion of light-colored clothes (q)
$0 < R_7 \leq 0.11$	10%
$0.11 < R_7 \leq 0.37$	20%
$0.37 < R_7 \leq 0.65$	30%
$0.65 < R_7 \leq 0.83$	40%
$0.83 < R_7 \leq 0.93$	50%
$0.93 < R_7 \leq 1$	60%

We denote by LC_{hh}^m the quantity of light-colored clothes to be washed per month by a household, and by DC_{hh}^m the quantity of dark-colored clothes to be washed per month by a household. These two quantities are determined as shown in equations 5.7 and 5.8.

$$LC_{HH}^m = q \times QC_{HH}^m \quad (5.7)$$

$$DC_{HH}^m = (1 - q) \times QC_{HH}^m \quad (5.8)$$

5.3.3.3 Quantity of linens per household

The weight of linen as a function of household type was given earlier in section 2.1. We denote by QL_{HH} the total weight of linens per household. Once the household type is determined, QL_{HH} is deduced from Table 5.2.

According to survey results, people wash their linens either once (50%) or twice per month (50%). We denote and by CR_l the changing rate of linens per month. A random variable R_g is generated uniformly and CR_l is determined as shown in Table 5.16.

Table 5.16: Random process for determining CR_l

Condition of the random variable R_g	Changing rate of linens per month (CR_l)
$0 < R_g \leq 0.5$	1
$0.5 < R_g \leq 1$	2

The total quantity of linens washed by households per month, denoted by QL_{HH}^m , is thus estimated from equation 5.9.

$$QL_{HH}^m = QL_{HH} \times CR_l \quad (5.9)$$

Where QL_{HH} represents the quantity of linen owned by a household, and CR_l is their changing rate per month.

As a result, the total service unit per household for the activity “washing laundry” comprises thus the monthly quantities of light-colored clothes LC_{HH}^m , dark-colored clothe DC_{HH}^m , and linens QL_{HH}^m . The modeling process for calculating this service unit is illustrated in Figure 5.8.

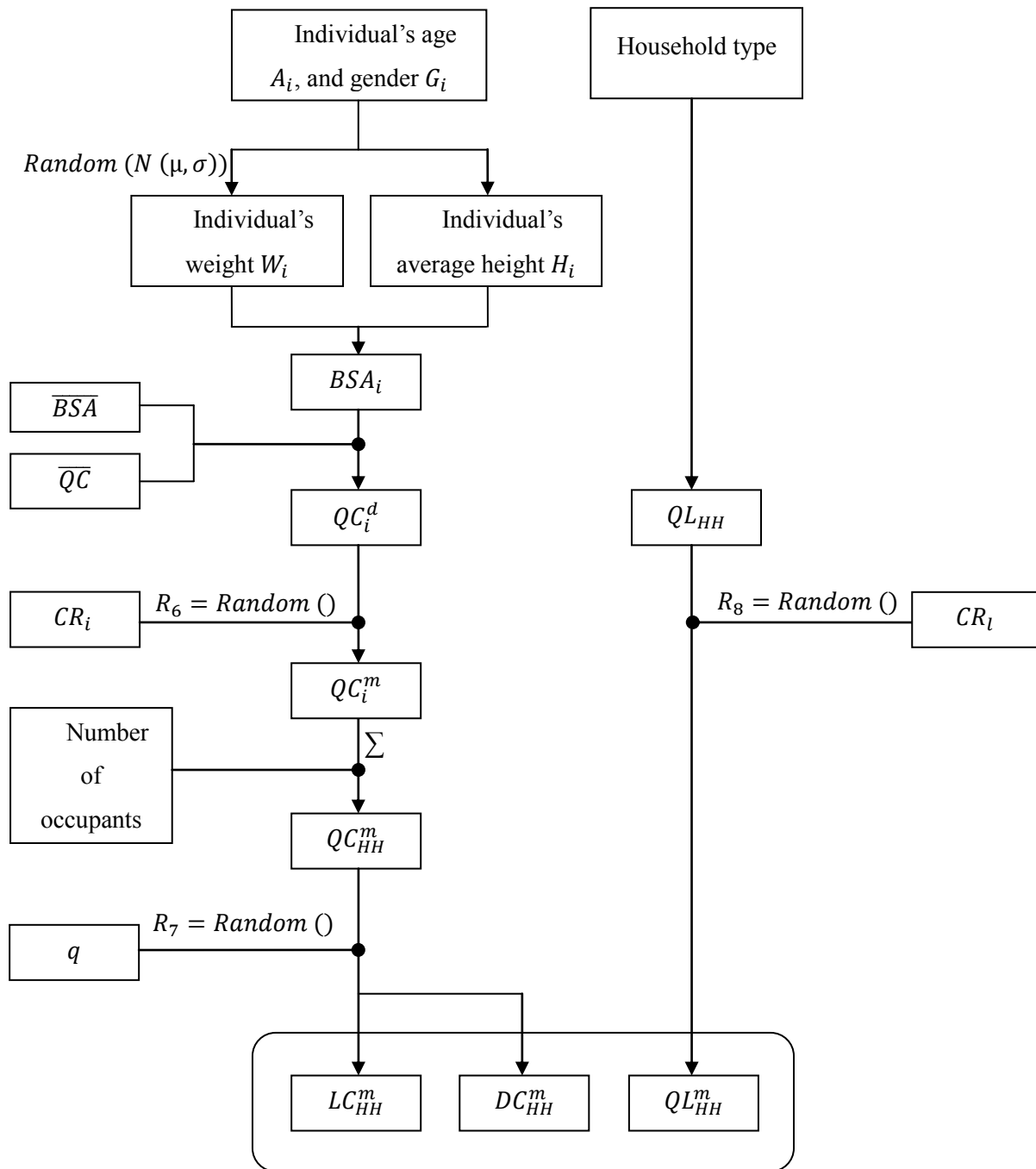


Figure 5.8 : Modeling process for determining the service unit of the activity “washing laundry”

5.3.4 Calculating energy and water consumption

The first step for calculating energy and water consumption is to determine the washing temperature and the filling rate.

5.3.4.1 Determining filling ratio

We denote by FR to be the filling ratio of washing machine's drum. During a simulation, a household is attributed a filling ratio randomly using the probability distribution shown earlier in Table 5.8. A random variable (R_9) is generated and the filling ratio FR is estimated as shown in Table 5.17 below. The same filling ratio is used for all washing loads for a given household.

Table 5.17: Random process for determining machine's filling rate

Condition of the random variable R_9	Filling rate (FR)
$0 < R_9 \leq 0.06$	60 %
$0.06 < R_9 \leq 0.1$	70 %
$0.1 < R_9 \leq 0.34$	80 %
$0.34 < R_9 \leq 0.77$	90 %
$0.7 < R_9 \leq 1$	100 %

As for the temperature setting , it depends on the sorting of laundry by a given household. If a household doesn't sort laundry, then the setting temperature used is the same for all laundry categories (light-colored, dark-colored, and linens), else three temperature settings are used. In order to account for this factor, a random number R_{10} is generated to determine whether a household sort or not the laundry as shown in Table 5.18.

Table 5.18: Random process for determining sorting factor

Condition of the random variable R_{10}	Sorting
$0 < R_{10} \leq 0.86$	Yes
$0.86 < R_{10} \leq 1$	No

Consequently, temperature settings are drawn randomly from the probability distributions of temperatures given earlier in Table 5.6 (in case of sorting) and Table 5.7 (no sorting). This is explained in the following section.

5.3.4.2 Determining washing temperature

- **Case one: Sorting**

In the case of sorting, we denote by T_1 , T_2 and T_3 to be the washing temperature for light-colored clothes, dark-colored clothes and home linens respectively. During simulation, three

random numbers (R_{11} , R_{12} , and R_{13}) are generated and the washing temperatures T_1 , T_2 and T_3 are estimated from the aforementioned distributions in Table 5.6. The random process for determining washing temperatures is summarized in Table 5.19.

Table 5.19: Random process for determining washing temperatures T_1 , T_2 , and T_3

	Conditions for random variables R_{11} , R_{12} and R_{13}	Washing temperatures
T_1	$0 < R_{11} \leq 0.26$	30 °C
	$0.26 < R_{11} \leq 0.70$	40 °C
	$0.70 < R_{11} \leq 0.94$	60 °C
	$0.94 < R_{11} \leq 1$	90 °C
T_2	$0 < R_{12} \leq 0.48$	30 °C
	$0.48 < R_{12} \leq 0.92$	40 °C
	$0.92 < R_{12} \leq 1$	60 °C
T_3	$0 < R_{13} \leq 0.13$	30 °C
	$0.13 < R_{13} \leq 0.43$	40 °C
	$0.43 < R_{13} \leq 0.95$	60 °C
	$0.95 < R_{13} \leq 1$	90 °C

- **Case two: No-sorting**

We denote by T_0 to be the washing temperature used in the case of no-sorting. The value of T_0 is determined randomly (R_{14}) from the probability distribution presented earlier in Table 5.7. This is illustrated in Table 5.20.

Table 5.20: Random process for determining T_0

Condition of the random variable R_{14}	Washing temperature T_0
$0 < R_{14} \leq 0.47$	30 °C
$0.47 < R_{14} \leq 0.87$	40 °C
$0.87 < R_{14} \leq 1$	60 °C

Once the washing temperature is known, the corresponding machine's power consumption is then deduced from Table 5.11.

5.3.4.3 Electricity and water consumption

- **Case one: Sorting**

For the reasons explained previously concerning the sorting case, we divide the total energy and water consumption of the activity “washing laundry”, denoted by EC_{wm} and WC_{wm} respectively, into three parts (consumptions) as shown in equations 5.10 and 5.11.

$$EC_{wm} = EC_1 + EC_2 + EC_3 \quad (5.10)$$

$$WC_{wm} = WC_1 + WC_2 + WC_3 \quad (5.11)$$

Where EC_1 and WC_1 represent the electricity and water consumed for washing light-colored clothes respectively. EC_2 and WC_2 represent the energy and water consumed for washing dark-colored clothes respectively. EC_3 and WC_3 represent the energy and water consumed for washing home linens respectively.

5.3.4.3.1 Electricity and water consumed for washing light-colored clothes

The energy consumed for washing light-colored clothes EC_1 is estimated through equation 5.12.

$$EC_1 = NC_1 \times P_{wm,T_1} \quad (5.12)$$

Where P_{wm,T_1} is the power consumption of the washing machine per cycle at a washing temperature T_1 (already determined in section 3.2), and NC_1 represents the number of washing cycles of light-colored clothes, and calculated as shown in equation 5.13.

$$NC_1 = \frac{LC_{HH}^m}{FR \times C_{wm}} \quad (5.13)$$

Where LC_{HH}^m is the quantity of light-colored clothes to be washed (calculated in equation 5.6), C_{wm} is the washing machine’s capacity (determined in section 3.2.2), and FR is the filling ratio of the machine.

The water consumed for washing light-colored clothes is estimated as shown in equation 5.14.

$$WC_1 = NC_1 \times \tilde{W} \quad (5.14)$$

Where \tilde{W} is the average water consumption per cycle, determined in section 3.2.

5.3.4.3.2 Electricity and water consumed for washing dark-colored clothes

The energy consumed for washing dark-colored clothes EC_2 is estimated through equation 5.15.

$$EC_2 = NC_2 \times P_{wm,T_2} \quad (5.15)$$

Where P_{wm,T_2} is the power consumption of the washing machine per cycle at a washing temperature T_2 (already determined in section 3.2), and NC_2 represents the number of washing cycles of dark-colored clothes, and calculated as shown in equation 5.16.

$$NC_2 = \frac{DC_{HH}^m}{FR \times C_{wm}} \quad (5.16)$$

Where DC_{HH}^m is the quantity of dark-colored clothes to be washed, which was determined in equation 5.7, C_{wm} is the washing machine's capacity, and FR is the filling ratio of the machine.

The water consumed for washing dark-colored clothes is estimated as shown in equation 5.17.

$$WC_2 = NC_2 \times \tilde{W} \quad (5.17)$$

Where \tilde{W} is the average water consumption per washing cycle, determined in section 5.3.2

5.3.4.3.3 Electricity consumption for washing linens

The energy consumed for washing home linens EC_3 is estimated through equation 5.18.

$$EC_3 = NC_3 \times P_{wm,T_3} \quad (5.18)$$

Where P_{wm,T_3} is the power consumption of the washing machine per cycle at a washing temperature T_3 (already determined in section 3.2), and NC_3 represents the number of washing cycles of linens, and calculated as shown in equation 5.19.

$$NC_3 = \frac{QL_{HH}^m}{FR \times C_{wm}} \quad (5.19)$$

Where QL_{HH}^m is the quantity of linens to be washed (determined in equation 5.8), C_{wm} is the washing machine's capacity (determined in section 3.2.2), and FR is the filling ratio of the machine.

The water consumed for washing home linens is estimated as shown in equation 5.20.

$$WC_3 = NC_3 \times \tilde{W} \quad (5.20)$$

Where \tilde{W} is the average water consumption per washing cycle, determined in section 3.2.

- **Case two: No-sorting**

In the case where a household do not sort laundry, the calculation of energy and water consumption is easier since only one washing temperature is used. The electricity consumed for washing laundry EC_{wm} is given by equation 5.21.

$$EC_{wm} = NC_0 \times P_{wm,T_0} \quad (5.21)$$

Where the number of cycles NC_0 is calculated through equation 5.22:

$$NC_0 = \frac{LC_{hh}^m + DC_{hh}^m + QL_{hh}^m}{FR \times C_{wm}} \quad (5.22)$$

Where P_{wm,T_0} is the power rating of the washing machine at temperature T_0 , and the latter is the temperature in the case of no sorting, determined in the previous section.

The water consumed for washing laundry is estimated as shown in equation 5.23.

$$WC_0 = NC_0 \times \tilde{W} \quad (5.23)$$

Where \tilde{W} is the average water consumption per washing cycle, determined in section 3.2.

It must be noted that the energy consumption for the standby mode is not considered for this activity. The reason is that the energy consumption of a washing machine during standby mode is almost negligible with respect to that during the functioning mode (Eneritech et al., 2008).

5.3.5 Running simulations

Given the probabilistic nature of our model, the variables are generated randomly from uniform distributions. In order to account for this randomness, a Monte Carlo technique is used for running simulations in a way that for each run, a different combination of variables and thus different consumption values are obtained. The number of iterations (taken initially as ten thousand) depends on the convergence of the results towards satisfactory values.

5.4 Testing model functionalities through simulation examples

For testing the functionality of the model as well as the validity of the results obtained, we perform a number of simulation examples for the three use-cases of the model. A short recall is given below for these three cases (refer to section 4.3 in chapter 4 for the detailed description of the use-cases).

5.4.1 Use case 1: simulating energy consumption for a specific household

First of all, the model can be used to quantify the energy consumption of a given activity (here “washing laundry”) for a **given specific household** taken as input. For each simulation, a specific household is defined **manually** by the user at the entry of the model.

For running simulation examples, we consider the same five household examples taken in chapter 4. These households are described hereafter.

5.4.1.1 Household examples considered

- **Household 1:** Single person, male, aged 32, active employed, senior profession, with a long-term education level and an income of 2700 Euros/month.
- **Household 2:** Couple without children. Adult 1 is a male aged 37, active employed, senior profession, with long-term educational level and an income of 3000 Euros/month. Adult 2 is a female aged 34 years old, active and employed, middle level professions, with short-term higher education and income of 2300 Euros/month.
- **Household 3:** Couple with 3 children. Adult 1 is a male aged 45, active employed, clerical and service-staff profession, with a baccalaureate level education and an income of 2000 Euros/month. Adult 2 is a 40 years old female, non-active housewife, with a baccalaureate level education and no salary. The first child is a 9 years old girl,

whereas the second and third are boys with 14 and 6 years old respectively. All children go to school.

- **Household 4:** One-parent family with one child. The parent is a 34 years old female, active employed in a middle level profession, with a short-term education level and an income of 1400 Euros/month. The child is a 5 year old boy who goes to school.
- **Household 5:** A couple of retired persons without children. Adult 1 is 66 years old male, inactive retired, Short-term higher education level, and an income of 1300 Euros/month. Adult 2 is a 62 years old female, inactive retired, Baccalaureate education level, and without income.

5.4.2 Use case 2: Randomly chosen household type with constraints

For the second use case, the model can be used to quantify energy consumption of a given activity (here “washing laundry”) for a **random household** taken at the input. The advantage here is that while generating this random household, we can give some **constraints** on its attributes. This is an important feature which enables testing variability between households having one or more criteria (attributes) in common.

5.4.3 Use case 3: Randomly chosen population of households

For this third use-case (third functionality of the model), a population of households can be generated randomly by the model. The energy consumption resulting from this third use-case can thus be representative of the total French population. Hence, simulation results can be compared to population-wise real energy consumption data in order to validate the model.

5.5 Results and discussions

First of all, to allow a better understanding of the different variables included in the model of the activity “washing laundry”, a simple simulation example is executed and presented, where a one single iteration is performed (one run and one iteration). The simulation is performed for ‘use case 1’, where the household example considered is household 3.

5.5.1 Results for one-single simulation (a guiding example)

First, the service units for all individuals of household 3 are calculated and illustrated in Table 5.21, where W_i is the weight of the individual, H_i is the height in cm, BSA_i is the body surface area in m^2 , QC_i^d is the quantity of clothes dressed by individual per day, CR_i is the changing

rate of clothes (1= daily, 2= once every two days, etc.), and QC_i^m is thus the quantity of clothes dressed by the individual per month.

Table 5.21: Quantity of laundry clothes per household per individual per month

Individual	W_i (Kg)	H_i (cm)	BSA_i (m ²)	QC_i^d (Kg/day)	CR_i	QC_i^m (Kg/month)
Parent 1	71.88	175	1.86	1.14	4	8.60
Parent 2	54.46	163	1.56	1.11	3	11.16
Child 1	21.75	129	0.87	0.62	1	18.64
Child 2	65.10	159	1.70	1.05	2	15.76
Child 3	19.77	114	0.78	0.48	1	14.56

The characteristics of the washing machine owned by the household are presented in Table 5.22, where C_{wm} is the machine's capacity, EL_{wm} is its energy label, $P_{wm,60^\circ C}$ is the power consumption for a washing cycle at 60 °C, and \tilde{W} is the water consumption in liters per cycle.

Table 5.22: Washing machine characteristics

C_{wm} (Kg)	EL_{wm}	$P_{wm,60^\circ C}$ (KWh/cycle)	\tilde{W} (Liters/cycle)
5	F	1.936	100

The values of the main determinant variables of energy consumption of the activity “washing laundry” for household 3 are illustrated in Table 5.23.

Table 5.23: Results of main determinant variables of energy consumption (household 3)

Variable		Value
Sorting of laundry?	s	Yes
Filling rate of washing machine	fr	80 %
Total quantity of clothes per household	QC_{HH}^m	68.74 Kg
Proportion of light-colored clothes	q	20 %
Quantity of light-colored clothes per household	LC_{HH}^m	13.74 Kg
Quantity of dark-colored clothes per household	DC_{HH}^m	54.99 Kg
Quantity of linens laundry per household	QL_{HH}^m	16.9 Kg
Number of washing cycles for light-colored clothes	NC_1	4 cycles/month
Number of washing cycles for dark-colored clothes	NC_2	14 cycles/month
Number of washing cycles for linens	NC_3	5 cycles/month

Temperature used for washing light-colored clothes	T_1	60 °C
Temperature used for washing light-colored clothes	T_2	30°C
Temperature used for washing linens	T_3	60°C

Once all model variables are determined, the electricity and water consumptions can be estimated. Simulation results for household 3 (for one iteration) are presented in Table 5.24.

Table 5.24: Energy and water consumptions of the activity “washing laundry” for household 3

Total number of cycles (cycles/month)	Total electricity consumption (KWh/month)	Total water consumption (Liters/month)
23	30.98	2300

A number of simulations are then performed according to the three use-cases defined in the previous section. The results describing energy consumption for the activity “washing laundry” for each use-case are presented in the following.

5.5.2 Results for use case 1

The model is used to estimate energy and water consumption for each of the five households presented in the previous section. For each household, 10000 simulations are performed. The results are summarized in Table 5.25.

Table 5.25: Average consumption results from 10000 simulation runs (use case 1)

	Average total number of cycles (cycles/month)	Average total electricity consumption (KWh/month)	Average total water consumption (Liters/month)
Household 1	9	6,26	556
Household 2	14	9,60	849
Household 3	26	18,47	1672
Household 4	12	10,68	968
Household 5	15	14,02	1309

Average results in Table 5.25 show that household 3 (couple with three children) has the highest consumption values compared to other households. This result is normal since the number of occupants in this household (5 occupants) is higher than in others. Household 1

presents the lowest consumption values. We notice that the number of cycles increases with the increase in the number of occupants, and such do the energy and water consumption.

For household 3, we can notice the difference between the results presented in Table 5.25 (for 10000 simulations) compared to those shown earlier in Table 5.24 (one simulation only). The number of washing cycles is higher while electricity consumption is lower. This difference is due to the large number of simulations taken in the second case, which yielded more averaged and representative results. In Figure 5.9, we plot the increasing cumulative frequency of electricity consumption, resulting from 10000 simulation runs, for the five households.

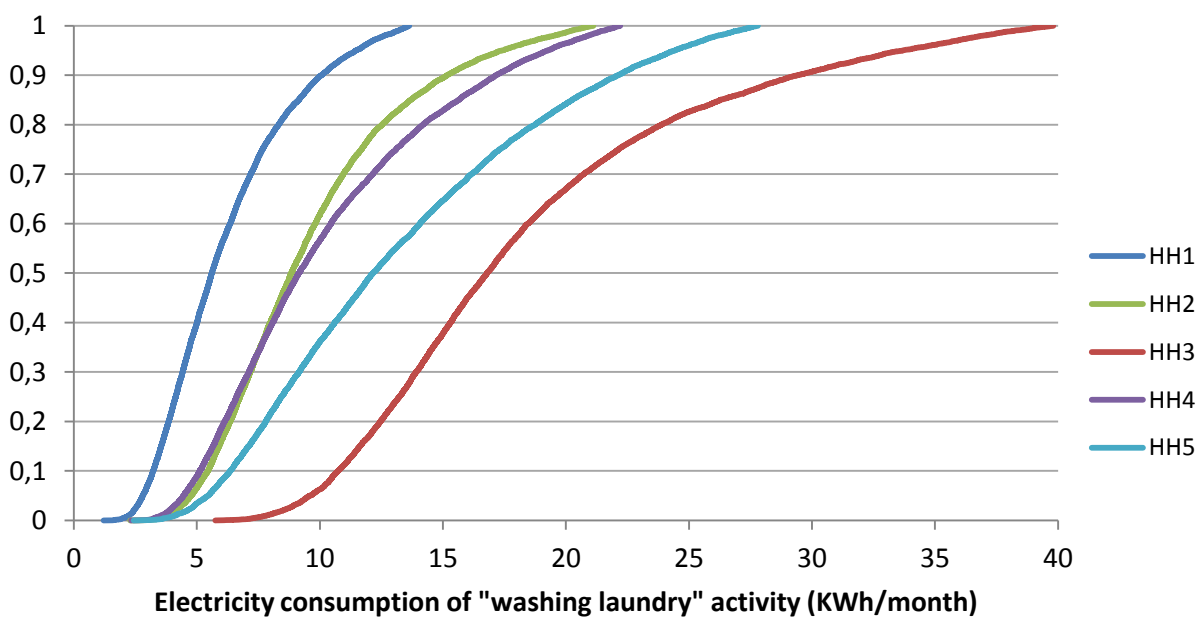


Figure 5.9 : Cumulative distribution of energy consumption of the activity “Washing laundry” for the five households (KWh/month)

The plot in Figure 5.9 shows again that the highest energy consumption values for the activity “washing laundry” are yielded by household 3. The maximum consumption of this household reaches 39.85 KWh/month, whereas it reaches 34.01 KWh/month, 25.48 KWh/month, 21.11 KWh/month, and 14.56 KWh/month for households 5, 4, 2 and 1 respectively. These results indicate that the electricity consumption of the “washing laundry” activity increases with the increase in the number of occupants within households.

Households 2, 4 and 5 have the same number of occupants (2 occupants), yet they reveal different average electricity consumptions of 9.60, 10.68 and 14.02 KWh/month respectively

(Table 5.25). This difference can be explained by the different family compositions between adults and children. Moreover, the difference may be attributed (indirectly) to households' socio-demographic attributes. The latter influence the ownership rates and the characteristics of washing machines present in households. This relation between household attributes and their energy consumption is further discussed for second use case below.

5.5.3 Results for use case 2

For this use case, random households are taken at the model input, where constraints can be defined on their attributes. Having in mind that any type of constraints can be applied using the model, we present here only two simulation guiding examples. In the first example, we consider a constraint on the household type, whereas in the second one we take two constraints respectively on the household type and the number of children per household.

5.5.3.1 Use case 2- Example 1

This example is the same as that applied for the activity “watching TV”. We perform simulations by giving a constraint on the **household type** (Single, couples with children, couples without children, one-parent families). For each household type, we perform 10,000 simulations. For each simulation, the model randomizes the attributes of each individual and then calculates the energy and water consumption yielded by the activity “washing laundry”.

Simulation results are illustrated in Table 5.26 through their descriptive statistics: mean(μ), minimum (m), maximum (M), median(χ), and standard deviation (σ) for each household. The results are also illustrated through a box plot in Figure 5.10 to give a visual depiction of their distributions.

The results for the number of washing cycles show that that couples with children have the highest values with an average of 22 cycle/month, followed by one-parent families with 16 cycles/month, couples without children with 14 cycles/month, and finally singles with a mean of 8 cycles/month (Table 5.26). These results show higher number of washing cycles for larger households especially those having children. Electricity and water consumption follow also the same logic as for the number of cycles, with larger families showing higher consumption levels than smaller ones.

Table 5.26: Descriptive statistics for simulation results of use case 2

		Household type			
		Single	One-parent family	Couples without children	Couples with children
Number of iterations (n)		10,000	10,000	10,000	10,000
Number of cycles (per month)	m	2	4	5	6
	M	16	32	26	43
	μ	8	16	14	22
	σ	3	6	4	7
	χ	8	15	13	21
Electricity consumption (KWh/month)	m	1.30	2.75	2.49	3.55
	M	18.12	35.59	24.17	35.55
	μ	7.29	14.32	10.57	15.77
	σ	3.67	7.12	4.53	6.60
	χ	6.43	12.57	9.55	14.27
Water consumption (liters/month)	m	126	245	245	350
	M	1820	3720	2300	2660
	μ	663.85	1286.98	890.06	1127.75
	σ	398.59	785.00	500.60	480.06
	χ	546.00	980.00	693.00	1008.00

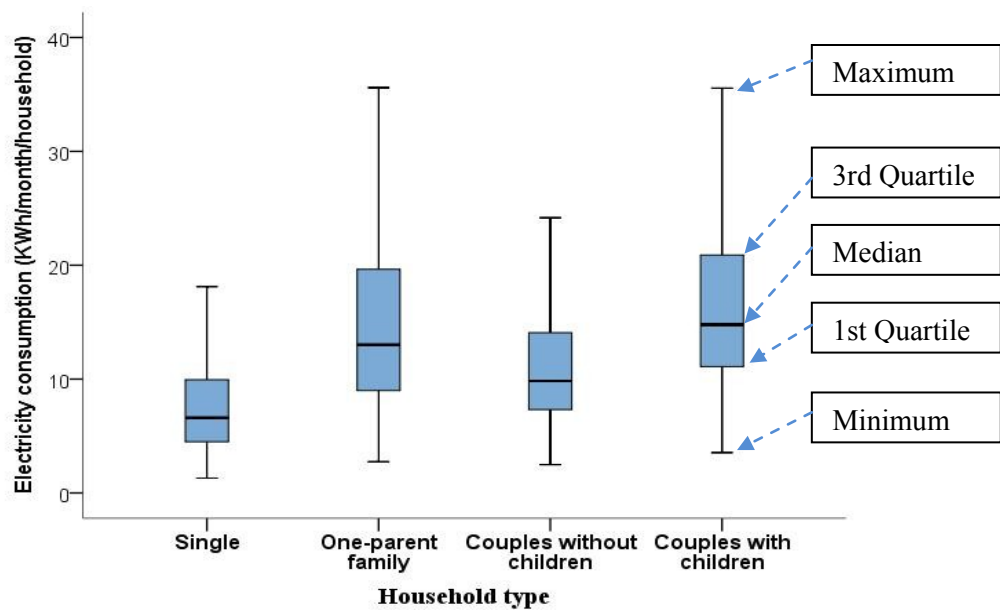


Figure 5.10 : Simulation results for the four household types (use case 2-Example 1)

The mean electricity consumed by couples with children for washing laundry is 15.77 KWh/month, which is higher than that consumed by one-parent families (14.32 KWh/month), by couples without children (10.57 KWh/month), and finally by singles (7.29 KWh/month).

These findings confirm the linear relation between the size of a household and its corresponding energy and water consumption for the “washing laundry” activity. Large households use more laundry (especially clothes), wash more frequently, and thus consume more energy and water.

5.5.3.2 Use case 2- Example 2

In this example, the model is used to examine energy consumption variation among a **homogenous sample** of households. For this example, we consider only households of “couples with children” type and we define the constraint on the number of children. The goal is to analyze consumption variation as a function of the number of children per household, for a given household type (here couples with children). The three cases considered are presented in Table 5.27.

Table 5.27: Number of children considered

Case	1	2	3
Number of children	[1,2]	[3,4]	[5,6]

For each case, ten thousand simulations are performed. For each simulation, the model randomizes the attributes of each individual and then calculates the corresponding energy consumption of the activity ‘washing laundry’ of the household.

Simulation results are illustrated through a box plot in Figure 5.11. As expected, energy consumption levels increase with the increase in the number of household occupants. Households with 5 or 6 children consume on average 26.76 KWh/month for washing laundry, which is 30 % higher than average energy consumed by households with 3 or 4 children (20.53 KWh/month), and 63 % higher than average energy consumed by households with 1 or 2 children (16.39 KWh/month).

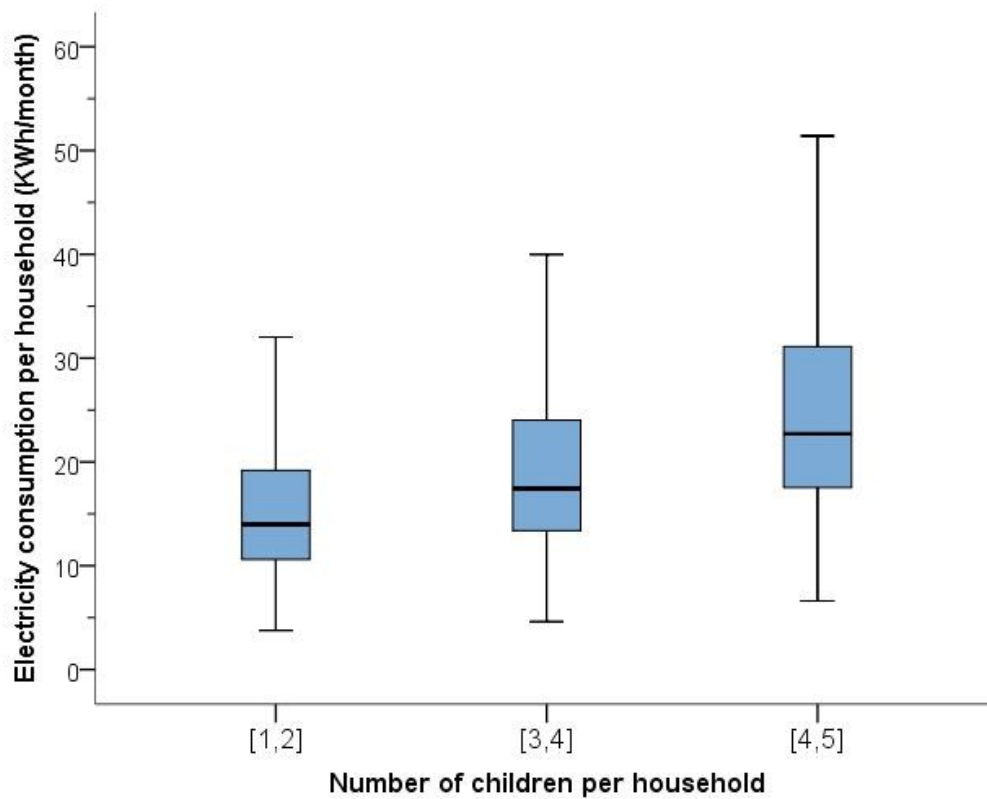


Figure 5.11 : Simulation results for the three cases (use case 2-example 2)

5.5.4 Results for use case 3

For this use case, ten thousand households are generated randomly and their corresponding energy and water consumption for the activity ‘washing laundry’ are calculated. Simulation results are presented in Table 5.28 and illustrated through box-plots in Figure 5.12 and Figure 5.13. Some outliers are present in simulation results; however their occurrence is minimal (around 300 out of 10000 simulation points), and thus are not represented in the plots.

Table 5.28: Descriptive statistics of simulation results for use case 3

		10,000 population-wise randomly chosen households	
Number of cycles (per month)	m	2	
	M	34	
	μ	14	
	σ	7	
	χ	13	
Electricity consumption (KWh/month)	m	1.54	
	M	28.05	
	μ	12.51	
	σ	5.66	
	χ	10.31	
Water consumption (liters/month)	m	112	
	M	2300	
	μ	871.30	
	σ	472.28	
	χ	770.00	

Results in Table 5.28 indicate that the average number of washing cycles per household is shown to be 14 cycles per month taking into consideration all household types (population-wise). The corresponding population-wise average electricity and water consumption for the activity “washing laundry” are respectively 12.51 KWh/household/month and 871.30 liters/household/month.

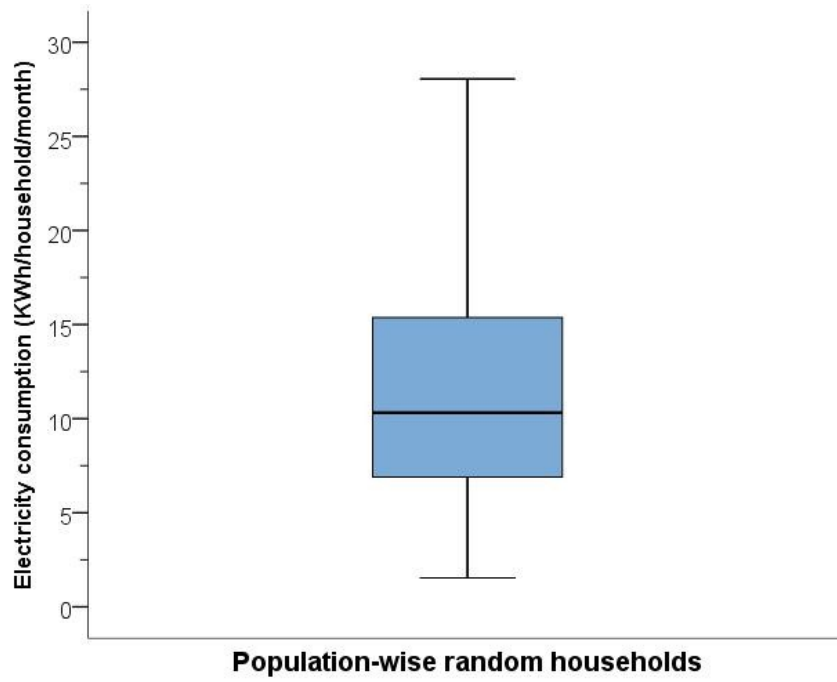


Figure 5.12 : Simulation results of electricity consumption for use case 3

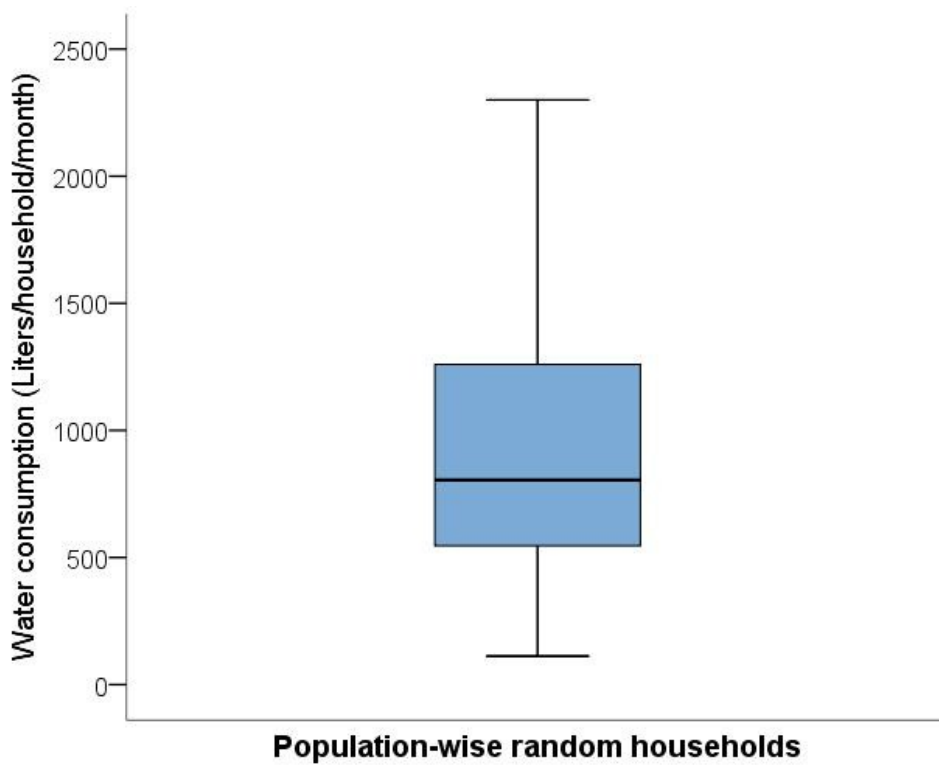


Figure 5.13 : Simulation results of water consumption for use case 3

5.6 Model validation

In order to validate the model proposed in this chapter, we compare its simulation results for the energy consumption of the activity ‘washing laundry’ against real measured data. Water consumption is not confronted here because of the lack in real data. The real data of energy consumption used by washing machines are taken from a French project called AEE2008⁸ (Enertech et al., 2008). In this study, energy consumptions of washing machines from 87 different households were monitored during a period of 44 days. The measurements show that the average annual electricity consumption per washing (per dwelling) is equal to 169 KWh/year. The extreme consumption values recorded were 850 KWh/year and 34 KWh/year. The histogram of electricity consumption of washing machines recorded by the study is shown in Figure 5.14. The mean electricity consumption is equal to 14.24 KWh/month (169 KWh/year) while the minimum and maximum consumption values are 2.89 and 70.83 KWh/month respectively.

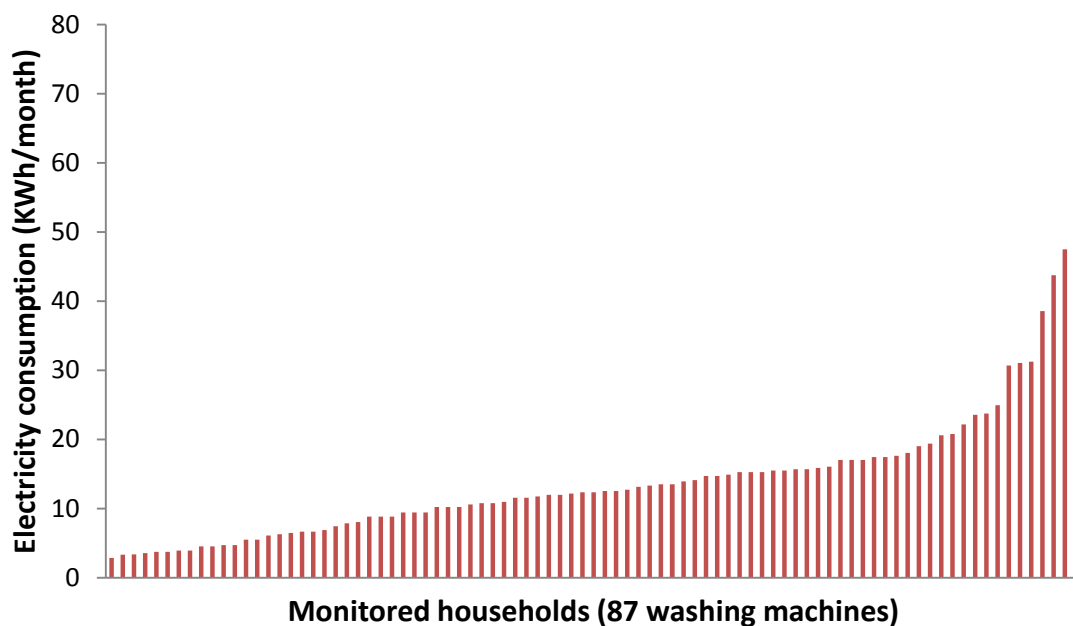


Figure 5.14 : Energy consumption of washing machines for each monitored household (Enertech et al., 2008)

⁸ This project was conducted by three important French organizations concerned in energy consumption within French residential buildings: ADEME, Electricité de France (EDF), and ENERTECH

In order to validate our model, we confront its simulation results to those of the study. Unfortunately, we cannot compare the results as a function of household types since we do not have information about household types surveyed in the AEE study, however population-wise consumption values could be used (according to model's use-case 3).

In order to achieve a fair comparison, the same measurement number as that of real data are needed, that is 87 simulation results. To get these, we first perform simulations for 10,000 random households (according to model's use-case 3). Then 87 households are chosen arbitrarily. It must be noted here that several samples (of 87 households each) can be randomly chosen from the 10000 simulation results in possession. For this reason, we performed a number of samplings (87 each) and we compared them to each other. The means (average energy consumption) for all samples are revealed to be very similar; however differences can be witnessed in the maximum and minimum values between different samples. The sample of randomly drawn 87 households considered is represented in Figure 5.15.

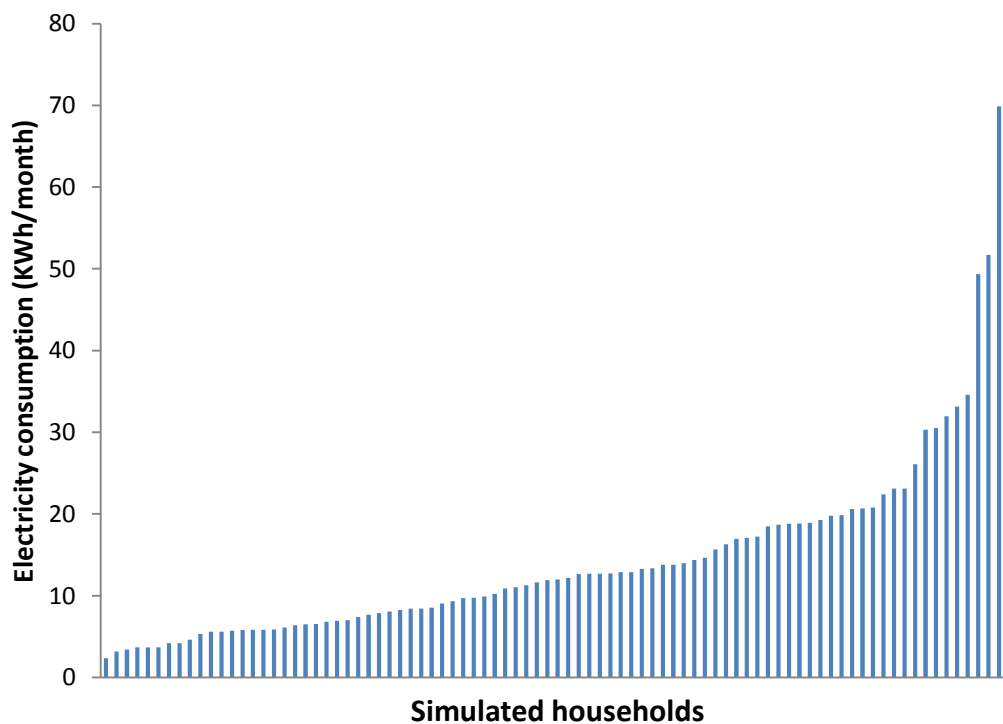


Figure 5.15 : Energy consumption results for simulated households

5.6.1 Validation through descriptive statistics

A first comparison between the energy consumption distribution of simulation results and that of real data is performed through their corresponding descriptive statistics as shown in Table 5.29. The mean values (μ) of both distributions seem to be close to each other with $\mu = 14.98$ KWh/month for simulation results and $\mu = 14.24$ KWh/month for real data.

Table 5.29: Comparing simulation results to real data through descriptive statistics (values are in KWh/month)

		Simulation results	Real data from (Enertech et al., 2008).
Energy consumption (KWh/month)	m	2.33	2.89
	M	77.41	70.83
	μ	14.98	14.24
	σ	12.98	10.46
	χ	11.99	12.37

The maximum consumption value for the real data ($M = 70.83$) is lower than that of simulation results ($M = 77.41$), while the minimum value is higher. The dispersion in consumption values for the two samples is almost the same. The descriptive statistics reveal high similarity between real data from one side and SABEC model simulation results from the other side.

5.6.2 Validation through statistical tests

In order to compare simulation results yielded from the model to real measured data taken from the study (Enertech et al., 2008), a non-parametric statistical test is performed similarly to what we have done for “watching TV” activity. We have chosen to compare both samples through a Mann–Whitney–Wilcoxon test which is a commonly used method especially for the case of independent and non-normal distributions. The test is performed using the SPSS statistical analysis software. We run the test with a 95% confidence interval. Test results are summarized in Table 5.30.

The p-value resulting from the test is equal to 0.809 which is favorable thus to retain the null hypothesis. This indicates that both samples have the same distribution of consumption values.

Table 5.30: Mann–Whitney-Wilcoxon test results

Null hypothesis	Test	Significance (p-value)	Decision
The distribution is the same across both samples	Mann–Whitney-Wilcoxon test	0.809	Retain null hypothesis

The results from this Mann–Whitney-Wilcoxon test, coupled with the descriptive statistics performed earlier, confirm the similarity of energy consumption distributions for the activity ‘washing laundry’ between simulation results from one side and real data from the other. These results emphasize the validation of model simulation results, and thus validate the SABEC model itself.

5.7 Conclusions

In this chapter, we apply the proposed SABEC model on the domestic activity “washing laundry”. First, a description of the activity is given and its different facets are discussed. The modeling logic is then presented and the main variables that influence energy consumption in this activity are exposed. Details on the statistical data considered, their nature and sources are presented and discussed. Then we demonstrate how the SABEC model can be applied to model and simulate energy and water consumption yielded by the subject activity. A number of simulation examples are undertaken in order to test the model’s functionalities. Simulation results are used to interpret the variation in energy consumption among different households. Finally, we validate the proposed model by testing the statistical significance of simulation results against real consumption data on a population-wide scale. The comparison of simulation results is done only for electricity consumption. Water consumption results are not confronted to real data due to the non-availability of reliable data about water consumption of washing machines in French households.

A part of the statistical data used in the model comes from reliable nation-wide studies. However, for some of these statistical data is taken from the web survey which we conducted on 105 households. The reliability of these of these, declared and not measured data, is still to be validated. This perspective can be achieved through larger scale surveys and measurement campaigns.

Chapter 6: Generalization of the modeling approach and its possible integration into the industrial context of residential buildings

In this chapter, various issues are tackled for generalizing the modeling and simulation method and making it practically usable in a professional context. We first discuss the applicability of the SABEC model on the different domestic energy end-uses and then a generalization approach is proposed. Second, we examine how the model can be simplified so that to reduce its complexity. For this sake, a variance-based sensitivity analysis on the model of the “washing laundry” activity is performed and major input variables are identified. Then, a simplification example is demonstrated. Third, we expose socio-behavioral approaches for modeling domestic energy and we discuss the possibility and interest of coupling qualitative social models with quantitative approaches such as that proposed in this thesis. Fourth, we summarize the different possibilities of how our model might be integrated into design context of buildings and what its future possible applications can be. Several of these applications are sketched and illustrated through examples.

6.1 The SABEC model in the whole framework of residential energy consumption

In chapter 2, we presented a complete breakdown structure of occupant-related energy consumption in residential buildings and which is recalled in Figure 6.1. As discussed previously, we are mainly interested in modeling energy consumption at the occupant and dwelling levels where the consumption is highly influenced by households’ attributes and lifestyles⁹. This influence is translated by appliance ownership rates and domestic activity patterns proper to each household. At the occupant level, different energy-consuming activities are identified on two scales which are aggregate (Food) and elementary (Cooking, eating, and dishwashing).

⁹ The determinants of energy consumption due to heating, cooling and ventilation are mainly attributed to building structural characteristics (Refer to chapters 1 and 2).

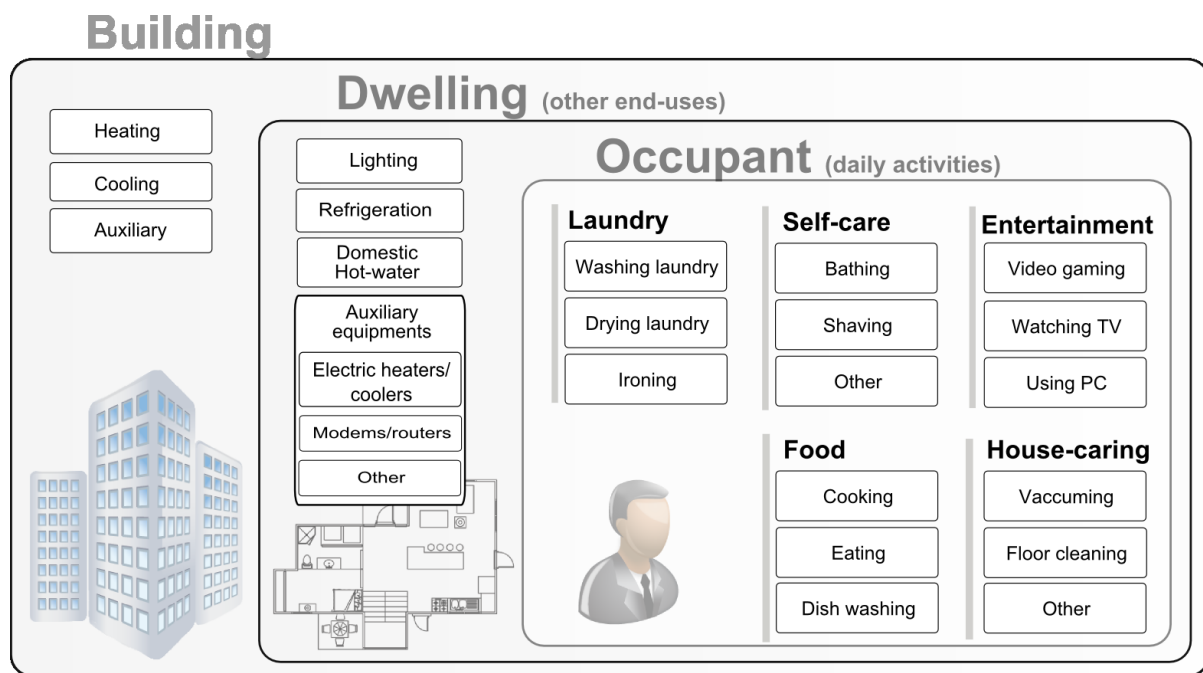


Figure 6.1: Systematic breakdown structure of energy consumption in residential building (from chapter 3)

The SABEC model presented earlier in chapter 3 is developed thus according to an activity-based approach. This means that the SABEC model's direct application is essentially aimed for modeling domestic activities at the occupant level. The model was demonstrated on two domestic activities which are watching TV (chapter 4) and washing laundry (chapter 5). Consequently, the issue of generalizing the SABEC model and its usage comes to mind: How the model can be applied for other domestic activities at the occupant level? And how can it be used in the whole framework for quantifying the total energy consumption of buildings? These questions are assessed in the following section.

6.1.1 Generalizing the SABEC model for other domestic activities at the occupant level

We propose a generalized architecture of SABEC model as shown in Figure 6.2. The probabilistic energy consumption spectrum of a household for a given activity is yielded at the output of the model. As shown in the figure, this energy consumption is calculated through two main blocks: (1) Activity patterns and (2) appliance ownership and characteristics. The determination of appliances' ownership and characteristics is done in term of probabilities which are calculated through correlating household attributes to probability

distributions coming from nationwide statistics (refer to section 3.3.2 in chapter 3). As for determining activity patterns, it comprises a number of steps as summarized hereafter.

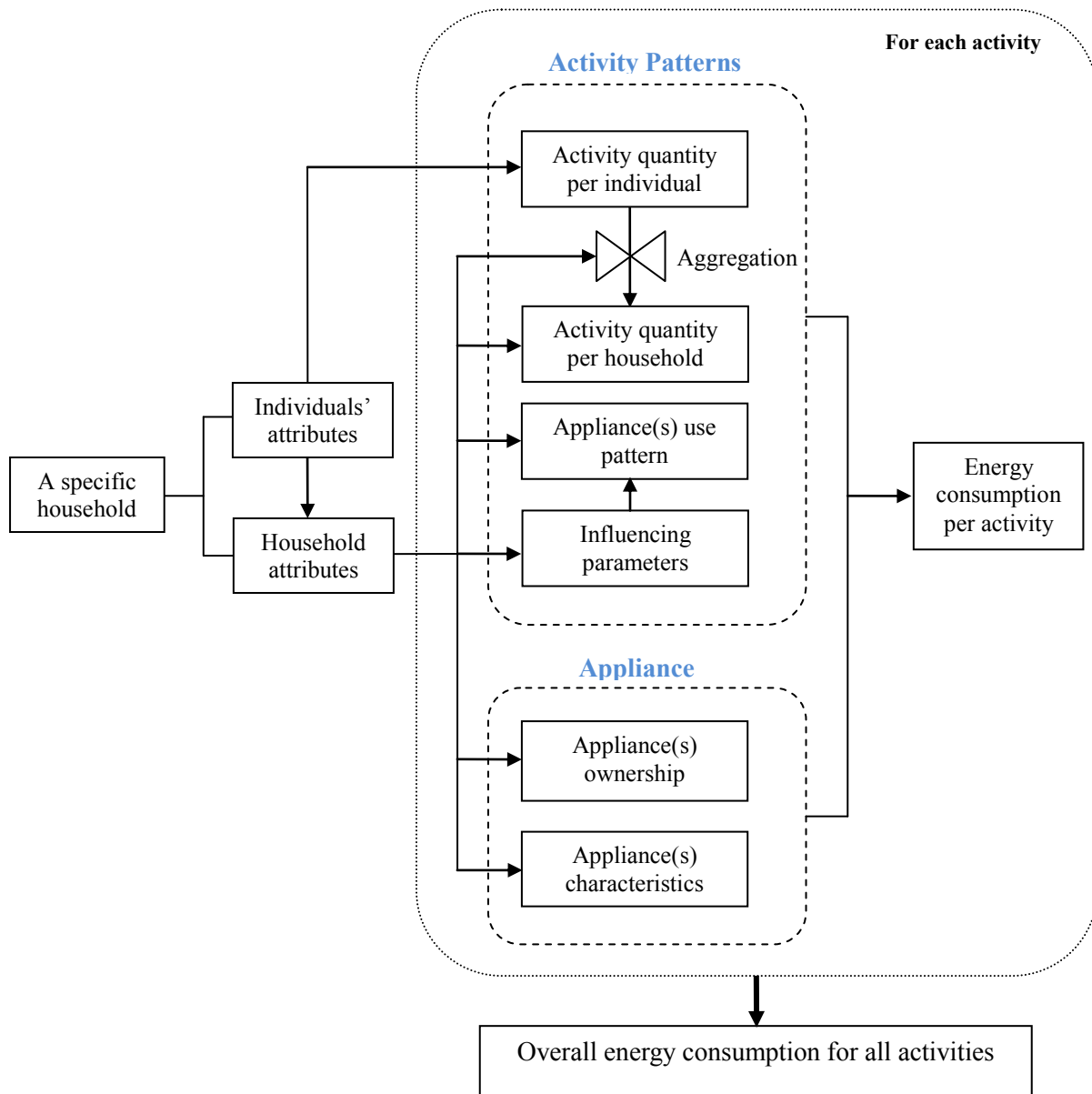


Figure 6.2 : General architecture of SABEC model

6.1.1.1 Quantifying activity's service unit at individual level

First a definition of the activity's service unit must be established. Second, the correlation between this service unit and some individual's attributes must be done. This is realized through scientific literature, statistical studies, and field data if possible. For instance, the service unit of "watching TV" activity is defined as the watching duration per day, which is found to be correlated to individuals' age, gender and socio-demographic category. As for

activity “washing clothes” activity, the service unit is defined as the quantity of clothes dressed by an individual (correlated to individuals’ age and weight) added to quantity of linens per household which is correlated to household type.

6.1.1.2 Quantifying activity’s service unit at the household level

This is done by defining a function for aggregating individual service units. This aggregation function depends on the nature of the activity, whether it is a shared or an additive one. For the sharing case, data can be obtained either from nation-wide surveys (as for the case of watching TV) or determined through meaningful heuristic logics which are further fitted to global national data of consumption.

6.1.1.3 Identifying the major parameters that influence the activity pattern

To better explain this point, we recall the modeling approach used for the example activity “washing laundry”, where a number of important influencing parameters are identified. For instance, variables such as the temperature setting, the percentage of light-colored clothes and the filling rate of the machine were used in the model.

According to the steps explained above, the SABEC model structure can thus be applied to any domestic activity, similarly to what was done for “watching TV” and “washing laundry” activities.

6.1.2 Dependency of service units of different activities at the occupant level

A last important point which must be accounted for is the possible dependency between service units of different activities. At the occupant level, some elementary activities may inherit their service units from other activities. This indicates a dependency relation. An example can be taken on the aggregate laundry activity as illustrated in

Figure 6.3 : if people wash a quantity of laundry (A_1), a proportional quantity will be dried (A_2), and a part of this quantity will be ironed (A_3). The service unit of the inheriting activity will thus be a function of its predecessors’.

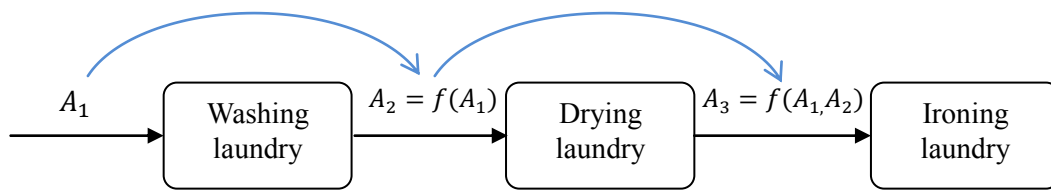


Figure 6.3 : Service unit dependency between activities

The same logic can be concluded for the “food” aggregate activity. This service unit dependency can simplify the quantification of energy consumption of some activities. For instance, the service unit of the activity « ironing laundry » can be plugged onto the activity « washing laundry », without being obliged to start from zero, but with considering some additional influencing parameters such as the percentage of ironed laundry over the total which can be related to household members attributes. A complete dependency framework of these intermediate and final service units would merit to be established, and it is thus one of our major research perspectives. For instance, an important intermediate service unit of the aggregate Food activity is the number of individual meals which depends of some household features as number of individuals and type of occupation (a student is likely not to have meals at home during weekdays but to be during weekends at home, a retired people is likely to have all the meals at home, etc).

6.1.3 Modeling energy consumption at the other levels

As mentioned before, the activity-based approach which is applied at the occupant level cannot be directly adapted for modeling energy consumption at all other levels¹⁰. The reason is that energy consumption at the dwelling and building level is not yielded by direct activities (such as washing or cooking), but it is rather due to transverse (widespread) activities such as lighting, heating and refrigeration. For example, lighting can be used while eating, reading, cooking, and even while sleeping. The same can be said about heating. Moreover, refrigerators are always turned on and their energy consumption is thus continuous (cooling cycles). At these levels (dwelling and building levels), the quantification of the service unit is not straightforward, and thus the SABEC model can be hardly applied. Nevertheless, relations between the energy consumption (electricity and water) quantified for activities at the

¹⁰ This was the main reason behind classifying energy consumption into different levels (Figure 1).

occupant level and those at the other levels can be established. For example, the consumption of domestic hot water (dwelling level) will be directly influenced by the water consumed at the occupant level for washing laundry, washing dishes, etc. In addition, widespread activities such as lighting are highly influenced by the service units of occupant-level activities such as “watching TV”, cooking, etc. The relationships between energy end-uses at the different levels are complex and not easy to establish. For instance, one can iron his/her laundry while watching TV and using lighting, or even more eat his/her dinner while listening to radio in the time where lighting and heating are turned on. The quantification of these relationships is not in the scope of this thesis; however it is a main issue to be investigated in future works.

The modeling of energy consumption at the dwelling and building levels necessitates considering additional number of variables especially those related to building characteristics. A number of such existing models were presented and discussed in chapter 2.

Case study: Depicting and modeling energy consumption of domestic lighting

In the context of our research work, we conducted a research study on the use pattern of domestic artificial lighting (Zaraket et al., 2012). An experimental protocol is developed to provide an observation diary to a number of volunteer households during two weekdays. The detailed description of the study and its results are published in the proceedings of IDETC/CIE 2012 conference. This article is added to this dissertation in Appendix C. Hereafter is a summary of this article.

The use of electric lighting is an important source of energy consumption in a building, and is considered as a transversal energy end-use which interferes in all aspect of daily energy consumption. In the context of our research work, we conducted an experimental survey to assess the use patterns of lighting in domestic dwellings (Appendix C). The main objective was to explore the key factors (socio-demographic, economic, technical and behavioral) responsible for the disparities in lighting consumption between one household and another. For this purpose, a micro level investigation protocol is elaborated and used to realize in-depth studies on a sample of 8 French households. Detailed diaries about lighting use were collected from the respondents along two weekdays.

The study reveals that the use of electric lighting in a dwelling is governed by various parameters related to buildings’ structural characteristics, light bulbs quality, and to occupants’ use patterns. The survey concludes the diffuse (widespread) use of lighting at

home. People use artificial lighting in order to satisfy their own visual comfort while performing daily life activities such as cooking, eating, reading, and house cleaning. Survey results suggest that the use of electric lighting is highly influenced by the socio-demographic and economic characteristics of households, their selection of lighting equipments, and their quantities of activities. For example, the results show that most households avoid purchasing LED bulbs due to their high price and relatively weak luminance.

The survey enabled us to have an idea concerning the major types of artificial lighting equipments that could be found in French dwellings, where we have identified five main types. These equipments are present in the dwelling either because they were installed by the landlord, or introduced by the tenant as for to compensate for the non-efficiency of the pre-existing lamps, or simply to be used as decoration. It has been found that lighting is used not only to gain better vision when natural light is dim, but also to adjust the ambience and the well-being of occupants. In this survey, we have distinguished the most important reasons for which occupants use lighting at home. A list of twenty different activities necessitating light usage is established. Of course, more similar qualitative studies are needed in order to get the full list of these activities. The results highlight as well the impact of design decisions on the consumption behaviors of households. For instance, the orientation of the dwelling and the lighting technologies installed by constructors can play a significant role in determining lighting consumptions. This paper validates the reliability of using in-depth studies for assessing energy demand in domestic buildings. Such exhaustive protocols can be very useful for understanding the ambiguous nature of occupant behaviors vis-à-vis building's energy consumption. Consequently, better design solutions could be proposed. The installation of energy-efficient lamps in rooms where the usage of light is more frequent (sitting room for example), and the integration of dimmer switches are good examples of design decisions that can be made. It is obvious that there exist some important correlations between lighting usage and consumption on the one hand, and the occupants' attributes (economic, social, cultural, lifestyle etc.) as well as the dwelling attributes on the other hand. For the purpose of establishing these correlations, further qualitative and quantitative studies must be conducted over larger samples and during longer periods in order to better understand the different lighting usage trends. This will lead to the development of more detailed lighting usage models, and possibly improve the predictability of global energy estimations in residential buildings.

6.1.4 Trade-off between model complexity and output quality

The approach developed and presented in this thesis aimed at a thorough modeling of occupant-related energy consumption. The proposed SABEC model considers exhaustively the influencing variables related to households, appliances, and activity patterns. The application of the modeling approach on two domestic activities revealed the complexity of the relationships existing between these variables, and their relative influence on the model output (energy consumption).

The next step is thus to apply the same modeling approach for other domestic activities. For this application to be more direct and efficient and for optimizing time and computational costs, further simplification of the model may be substantial. This way, the model can be better developed while **maintaining a sound balance between complexity and output quality**.

The first step of simplification would be to identify the most important influencing variables on the output of the model. This can enable overlooking some variables, and thus limiting the number of model's input variables. To discern which parameters have the most influence over model performance and to identify what the most appropriate parameter values are, we need to find a way to screen out sensitive parameters and quantitatively evaluate the influence of each parameter on model performance. Sensitivity analysis (SA) is an important quantitative technique which can be applied for this purpose.

Sensitivity analysis can identify parameters of which a reduction in uncertainty specification will have the most significant impact on improving model performance measures. Thus, if some non influential parameters can be identified and fixed reasonably at given values over their ranges, the computational cost may decrease without reducing model performance. Furthermore, sensitivity analysis can play an important role in model verification and validation throughout the course of model development and refinement. For more lecture about sensitivity analysis methods, the reader may refer to (Gan et al., 2014). As an example, we apply sensitivity analysis on the model proposed for the “washing laundry” activity.

The model for the “washing laundry” activity is developed by considering a relatively high number of variables related to households' attributes, “washing laundry” activity patterns, and appliance characteristics.

The variables related to households' characteristics taken at the input of the model are: Household type, number of occupants (adults and children), household's income, and age, education level, and socio-professional class of household's reference person. As detailed earlier in chapter five, each of these variables can influence the yielded energy consumption of the activity "washing laundry". However, it may be shown that some of these variables can have a higher influence on the model's output than the others.

6.1.4.1 Variance-based sensitivity analysis for model's input variables

Sensitivity analysis aims to describe how much model output values are affected by changes in model input values. The exact character of a sensitivity analysis depends upon the particular context and the questions of concern. In our case, the model is of a probabilistic nature. For such probabilistic models, variance-based global sensitivity analysis methods are very commonly applied (Most, 2012). In addition, the input variables of the proposed model are correlated to each other (socio-professional class and income for example), meaning that we are dealing with a model having dependent input variables.

A commonly used measure in sensitivity analysis is the so-called sensitivity index (also called Sobol index or correlation ratio). In this section, we present a brief description for calculating this index. For detailed reading about sensitivity analysis, please refer to (Baudin and Martinez, 2013; Frey and Patil, 2002; Frey et al., 2004; Mara and Tarantola, 2012, 2012; Saltelli and Bolado, 1998; Sobol, 2001).

The widely known measure used in sensitivity analysis is called the first order sensitivity index. It is used to compute the marginal contribution of each input factor to the variance of the output. First order sensitivity indices measure only the decoupled influence of each variable (without taking into account its interactions with other input parameters), an extension for higher order coupling terms is also developed. Another measure of sensitivity is called the total effect sensitivity indices, denoted by S_{T_i} which measures both individual effect of a variable X_i and the effect of its interaction with other input variables. Although several methods are developed to quantify higher order and total effect indices for the case of independent inputs, only very few methods are proposed for the case of dependent input models. Authors such as Mara and Tarantola (2012) and Most (2012), highlight that the application of such methods for models with dependent inputs is still time consuming and computationally expensive since they necessitate complex sampling methods and matrix combination approaches. For this reason, we shall limit the sensitivity analysis only to the

quantification of the first order sensitivity indices S_i . Hereafter is a description of the procedure for calculating the latter. This procedure has the advantage that it gives suitable estimates for independent and dependent input parameters (Most, 2012).

Assuming a model with an output Y as a function of a given set of m random input parameters X_i (Equation 6.1).

$$Y = fn(X_1, X_2, \dots, X_m) \quad (6.1)$$

The first order sensitivity index of Y to the variable X_i is denoted by S_i and calculated as in equation 6.2.

$$S_i = \frac{V_{X_i} \left(E_{X_{\sim i}} (Y/X_i) \right)}{V(Y)} \quad (6.2)$$

$V[\cdot]$ stands for variance operator and $E[\cdot/\cdot]$ for the conditional expectation operator. $V(Y)$ is the total variance of the model output Y , and $V_{X_i} \left(E_{X_{\sim i}} (Y/X_i) \right)$ is called the variance of conditional expectation with $X_{\sim i}$ denoting the matrix of all factors but X_i . $V_{X_i} \left(E_{X_{\sim i}} (Y/X_i) \right)$ measures the first order effect of X_i on the model output. The sensitivity index S_i measures thus the part of the variance which is caused by the uncertainty in X_i . This index is always positive ($S_i \in [0,1]$). A small value of S_i indicates little influence of the variable X_i on the variance of the output, while higher values indicate higher influence.

6.1.4.2 Application of variance-based sensitivity analysis for the “washing laundry” model

For the model of “washing laundry” activity, sensitivity analysis is performed on all elementary input variables related to household attributes so that to compute their marginal contribution to the variance of the output. These variables are: number of adults, number of children¹¹, household income, reference person’s age, socio-professional class, education level, and activity status. For each of these variables, the first order sensitivity index is estimated (as shown in previous section) by performing 10000 simulations. The results are presented in Figure 6.4.

¹¹ The household profile and the number of occupants are not elementary variables since they are derived directly from the number of adults and children.

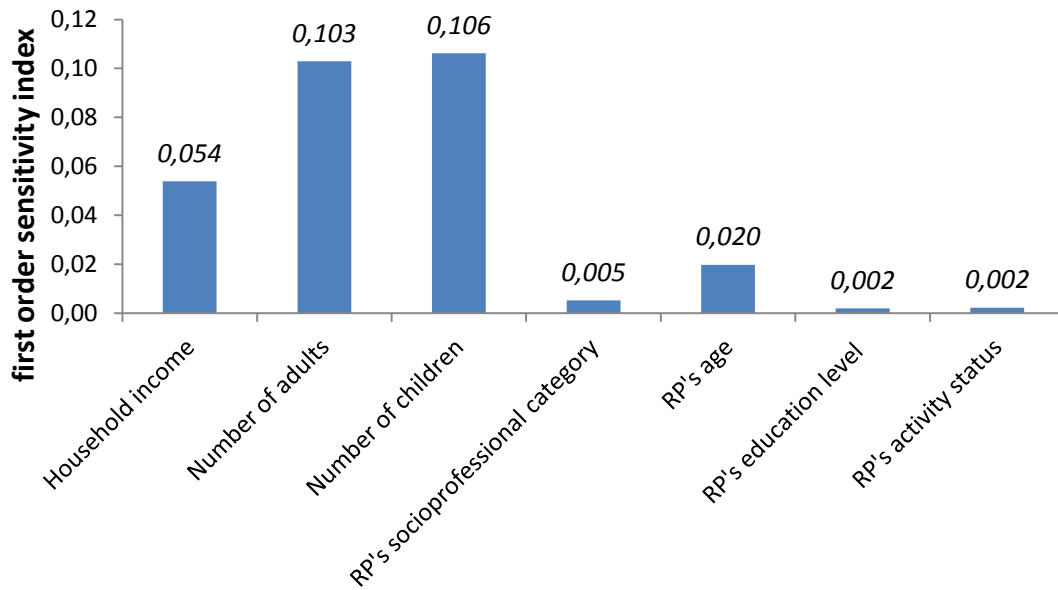


Figure 6.4 : First order sensitivity indices for the input variables of the “washing laundry” activity model

As shown in this figure, the variables “number of children” and “number of adults” show the highest sensitivity indices with values 0.106 and 0.103 respectively. These values indicate that around 10 % of the total variance of the output result is due to the uncertainty in each of the two input variables. The other remaining variables show smaller values of sensitivity index, revealing thus smaller influence on the variance of model’s output.

To better interpret these results, we recall from chapter five the important role of the two variables “number of adults” and “number of children” in the determination of the activity’s service unit (quantity of laundry per household per month). Therefore, they have direct influence on the quantity of energy consumed which explains their higher sensitivity indices than other variables. The “income” variable shows a sensitivity index of 0.05. According to the structure of the model (laundry activity), the income may influence the possession of appliances and their energy rating. The variables: reference person’s education level, socio-professional class, age, and activity status, may also influence on the possession rate of washing machines and their energy rating. Yet, they do not influence directly the activity’s service unit (refer to chapter 5). Therefore, their influence on the yielded energy consumption (model output) is smaller which explains their low sensitivity index values.

It must be noted again that the first order sensitivity indices estimated here represent only the influence of each variable individually, without considering the interactions with other input

variables. Future more-detailed analysis (higher order and total effect sensitivity index) of dependent-input models may reveal higher indices for these variables.

Moreover, we emphasize that sensitivity analysis was only performed for variables related to household attributes. Other model variables such as machine's filling ratio, ratio of white clothes and temperature setting are not considered in this sensitivity analysis experiment. The reason is that we aim here at testing only if we can simplify the number of household variables, and not all the variables of the model. Future work may include testing the importance of these variables.

6.1.4.3 Proposal of a simplified model for the “washing laundry” activity

The identification of the most influencing input variables through sensitivity analysis enables simplifying the model by reducing the number of its input variables without modifying its performance and precision. In this section, we present a simplification example of the model for the “Washing laundry” activity.

The sensitivity analysis conducted earlier show that the main input variables (related to household attributes) for the model of the “washing laundry” activity are the “number of adults” and “number of children”. Therefore, to simplify the model, these variables can be taken as representative of household attributes, and thus are used to estimate the service unit of the activity. According to French national statistics, the distribution of adults and children numbers per French household is given in Table 6.1. N_{ad} and N_{ch} stand respectively for the number of adults and number of children per household.

Moreover, the variables representing the activity patterns are also simplified¹². For each variable, we consider the weighted average value as shown in Table 6.2. The detailed description of these variables and their probability distribution was given chapter 5.

The same thing is also performed for the variables characterizing a washing machine where we consider the weighted average values for each variable as shown in Table 6.3. These average values are taken from statistical studies presented in details in chapter 5 (ADEME, 2012b; Enertech, 2008).

¹² Even though these variables were not considered in the sensitivity analysis, their simplification is done as a guiding example (for each variable, the weighted average value is used)

Table 6.1: Distribution of household composition (number of adults and children) for the French population

Household composition		Percentage in the French population (%)
Number of adults N_{ad}	Number of children N_{ch}	
1	0	33.5
2	0	26.1
1	1	5.2
1	2	1.9
1	3	0.6
1	4	0.2
2	1	14.3
2	2	12.4
2	3	4.9
2	4	1.0
Total	100 %	

Table 6.2: Simplified variables of activity patterns for the “washing laundry” activity

Variable	Value
Quantity of clothes used by adult per day (Kg)	1.2 Kg
Quantity of clothes used by child per day (Kg)	0.7 Kg
Changing rate of clothes per month for adults	16 times
Changing rate of clothes per month for children	22 times
Washing temperature for all laundry	60 °C
Mean weight of linens per household	12,625
Changing rate of linens per household per month	2

Table 6.3: Simplified variables of washing machine characteristics for the “washing laundry” activity

Variable	Value
Energy rating	A
Capacity C_{wm} (in Kg)	6
Energy consumption KWh/cycle at 60 °C	0.9
Water consumption Liter/Kg	67.5

The energy consumed by a household for washing laundry can thus be calculated as follows:

$$\begin{aligned}
 EC_{wm} &= \text{Number of cycles per household} \times \text{energy consumption per cycle} \\
 &= (\text{total laundry per household per month} / \text{Capacity}) \times 0.9 \\
 &= ((\text{total clothes per month} + \text{total linens}) / 5) \times 0.9 \\
 &= ((\text{total clothes per month} + 25.25) / 5) \times 0.9 \\
 &= (((16 \times 1.2 \times N_{ad} + 22 \times 0.7 \times N_{ch})) + 25.25) / 5) \times 0.9 \\
 &= (((19 \times N_{ad}) + (15 \times N_{ch}) + 25.25) / 5) \times 0.9
 \end{aligned}$$

Hence the simplified model can be written as in equation 6.3:

$$EC_{wm} = 3.42 \times N_{ad} + 2.7 \times N_{ch} + 4.55 \quad (6.3)$$

The energy consumption is thus given through a simple relationship between the number of adults and children per household. By using equation 6.3, we calculate the energy consumption yielded by the activity “washing laundry” for each combination of the number of adults and children. The results are summarized in Table 6.4. For example, case 2 (two adults and zero children) corresponds to households of type “couples without children”.

Table 6.4: Results of energy consumption for the activity “washing laundry” from the simplified model

Case	Household composition (N_{ad}, N_{ch})	Energy consumption (KWh/household/month)
1	(1, 0)	7.97
2	(2, 0)	11.39
3	(1, 1)	10.67
4	(1, 2)	13.37
5	(1, 3)	16.07
6	(1, 4)	18.77
7	(2, 1)	14.09
8	(2, 2)	16.79
9	(2, 3)	19.49
10	(2, 4)	22.19

Using the consumption data from Table 6.4 and the probability distribution from Table 6.1, we estimate the weighted average of energy consumption for the laundry activity yielded by the simplified model. This is equal to 11.9 KWh/month/household. We recall the mean of energy consumption for the total population estimated by the refined model in chapter 5 and

which was equal to 12.51 KWh/month. Both values seem to be very close to each other revealing thus good results for the simplified model.

A more detailed comparison of the results from both simplified and refined models is shown in Figure 6.5. The consumption values are estimated for both models as a function of the number of adults and children. The results from the simplified model (blue scatter plot) reflect the relationship between energy consumption and both the number of children and adults per household as was presented in equation 6.3. The impact of the number of children can be noticed by comparing for instance the results of cases 6 and 7. The consumption value for case 6 is equal to 18.77 KWh/month (1 adult and 4 children) which is higher than that of case 7 (2 adults and 1 child) equal to 14.09 KWh/month.

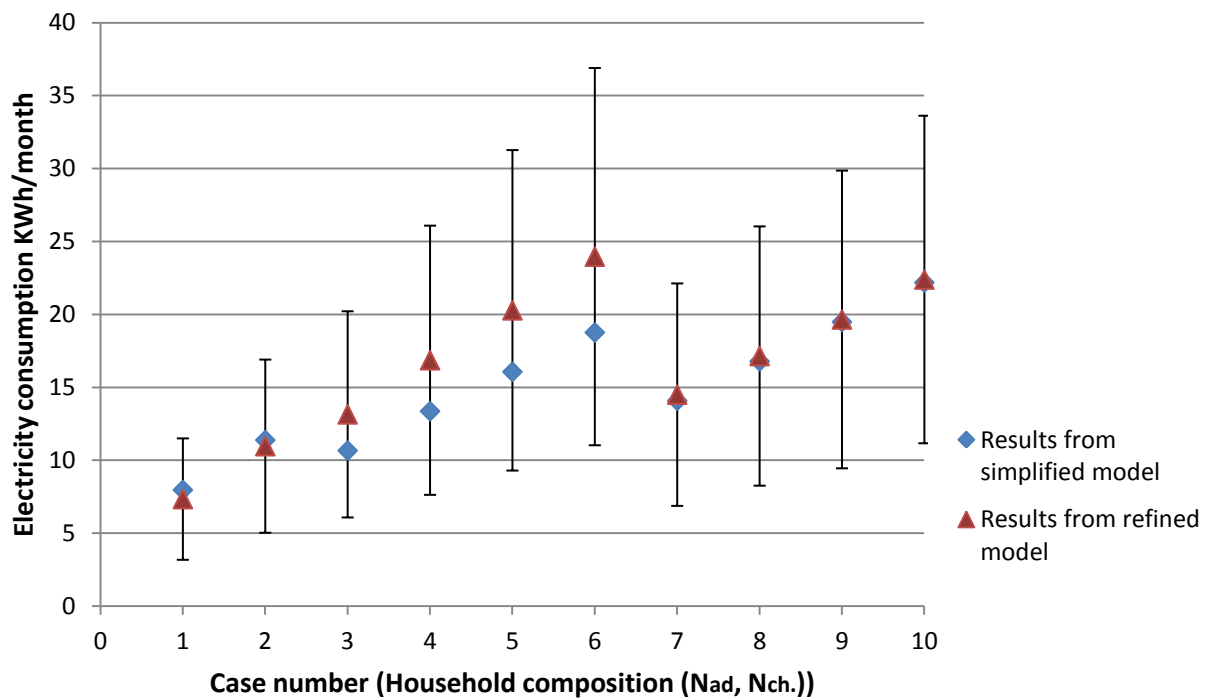


Figure 6.5 : Comparison between results from simplified and refined models for the activity “washing laundry”

Each result of the refined model (red scatter plot) represents the mean value of 10000 simulations performed for the corresponding case (number of adults and children). The error bars correspond to interval $[\mu + \sigma, \mu - \sigma]$. One can notice the increase of output values of the refined model as a function of the number of adults and children. This confirms the importance of both variables and their influence on the energy consumption for the laundry

activity as evoked earlier. The scatter plot in Figure 6.5 reveals the relative differences in the results of both refined and simplified model. The weighted average of the relative difference between results of both models is equam to 6.11 %. This value indicates that results from simplified model are very close to those of refined model.

As a conclusion of these results, we can say that the simplified model can deliver mean consumption values which correspond more or less to realistic consumption figures. Yet, the main advantage of the refined model is that it provides a detailed description of energy consumption by assessing the whole spectrum of possible values. As a conclusion of this case study, one can conclude the importance of conducting sensitivity analysis in order to simplify the model. However, this simplification must be conducted carefully by taking all the major influencing input variables into account.

6.2 Coupling qualitative socio-behavioral models to quantitative modeling approaches of energy consumption

As demonstrated through the different chapters of this thesis, socio-demographic and economic characteristics of occupants exert a substantial influence on buildings' performance during the use-phase. For this reason, a number of researchers from different social science fields are very interested in studying these complex relations between occupants and their living and consumption habits within residential buildings (refer to chapters 1 and 2). Socio-behavioral models can be very interesting for studying domestic energy consumption from a qualitative perspective. Such models allow categorizing the population into distinct archetypical personas where each of them is characterized by its own consumption profile and arbitration mechanisms. Such vulgarization of consumers' profiles may be beneficial in the case where detailed information about households' socio-demographic and economic attributes is not available.

In this section, we expose an example of such socio-behavioral approaches and we discuss the possibility/interest of coupling qualitative social models with quantitative approaches such as that proposed in this thesis.

6.2.1 Clustering occupants into different archetypical personas according to their energy consumption patterns

During our research work, we have been in contact with sociologists from the French scientific and technical centre for building (CSTB). These researchers in social sciences

conduct studies on the influence of different practices, rationalities and motivations of occupants on the energy consumption of residential edifices in France (Flamand and Roudil, 2013; Roudil et al., 2012). In their work, the authors identify three major structural drivers of occupants towards residential energy consumption. These drivers are economic resources, social norms, and material/technical culture of households. According to these three drivers, Roudil et al. cluster the French occupants into four different profiles, each having its own figure of arbitration and social practices towards domestic energy use. They distinguish between opportunist, rational, radical, and constrained profiles. For instance, Roudil et al. describe households of opportunist profile as those who do not give a special care to any of the three drivers mentioned earlier. Without changing their daily life and influencing their consumption patterns, these opportunist households use the best circumstances, at once, to undertake a process of energy sobriety, financial savings and maintain their comfort level. Rational households are almost similar to opportunists, with a difference that they seek often to rationalize their consumption due to economic drivers. As for the third profile, called radical, the authors conclude that this type of households is an especially paradoxical figure. The families take quite conscious discourse concerning environmental issues and energy sobriety; however they do not show willingness to give up a lifestyle where household equipment and access to home entertainment is considered substantial. These households impose on themselves high constraints, similar to an ecological radicalism, while allowing consumerist practices in other areas. The last profile, called constrained, is marked by a character of obligation. This type of households concerns mainly low-income ones. Being tenants in majority, they are captive to an economic situation that requires them to pay close attention to their energy bills. They monitor their consumption and have for instance a relatively restricted amount of use of multimedia and entertainment devices, which is also limited by the low possession ratio of domestic equipments (for example, only one TV and a single computer for the whole family with a limited time of use). Families of constrained profile develop practical sobriety reinforced by a discourse that emphasizes that energy use is not an essential need and that they can live without it.

In our opinion, such clustering of the population into different energy-related social profiles can be very beneficial for modeling and predicting energy consumption patterns in residential buildings. For instance, characterizing the future occupants of a building through these profiles can give a picture about their future energy consumption and thus can guide in the prediction of energy consumption and in some design and construction decisions.

According to sociology experts, the correlation between an energy-related social profile and household's attributes is not straightforward. This means that, for a given household with specific attributes, it is not possible to determine directly the corresponding energy-related social profile. Yet, this is not our main interest. The aim here is to use information about energy-related social profiles in order to establish a qualitative (and eventually quantitative) correlation between a given family, its energy-related social profile, and an energy consumption modulation range per type of domestic activities.

6.2.2 Coupling qualitative energy-related social models to quantitative approaches

In this section, we sketch how qualitative socio-behavioral approaches can be coupled with quantitative modeling approaches (such as the one proposed in this thesis) in order to better predict energy consumption behaviors in residential buildings. We emphasize here that the qualitative information that we are going to use hereafter is not in our possession right now, but it may be cognitively extracted by sociologist experts in future works¹³.

We suppose that we can be provided, by sociology experts, with some qualitative information about domestic energy consumption like as shown in Table 6.5 and Table 6.6. This information is given in the form of qualitative indicators expressing energy consumption modulations or activity quantities modulations for each socio-behavioral profile and per each domestic activity (Table 6.5). The probability distribution of the different profiles among the population is supposed to be known as in Table 6.7.

Table 6.5: Example of qualitative modulation of domestic energy consumption per social profile

	Opportunist	Rational	Radical	Constrained
Washing laundry	++	-	--	+
Cooking food	++	-	+	--
Watch TV	--	++	+	-

For example, qualitative information in Table 6.5 indicate the following: for washing laundry at home, households of rational profile have an average consumption compared to the population; radical households consume slightly less than the average; opportunist profile

¹³ We confirm here that such type of information can be retrieved from sociology experts, like the ones working for French CSTB institute.

consume energy significantly higher than other profiles, while constrained profiles are those who consume less energy for the same domestic activity.

Table 6.6: Qualitative indicators and their meaning

Qualitative Indicator	Qualitative information
+ +	Highest consumers
+	Above average consumers
0	Average consumers
-	Below average consumers
- -	Lowest consumers

Table 6.7: Distribution of the four archetypical profiles over the population (supposed values)

Energy-related social profile	Probability distribution among population
Rational	30 %
Radical	20 %
Opportunist	30 %
Constrained	20 %

In order to be converted into significant quantitative information in the SABEC model, these qualitative modulations must be transformed into quantitative modulations. An application example is given hereafter for the “watching TV” activity.

As seen in chapter 4, the average population-wise electricity consumption for this activity was equal to 3.95 KWh/household/week. The increasing cumulative distribution of energy consumption for the activity “watching TV” is (from chapter 4) is represented in Figure 6.6. Now, using the qualitative indicators from Table 6.5, and the probability distribution of each archetypical profile in Table 6.7, consumption intervals for each profile may thus be deduced as shown in Figure 6.6.

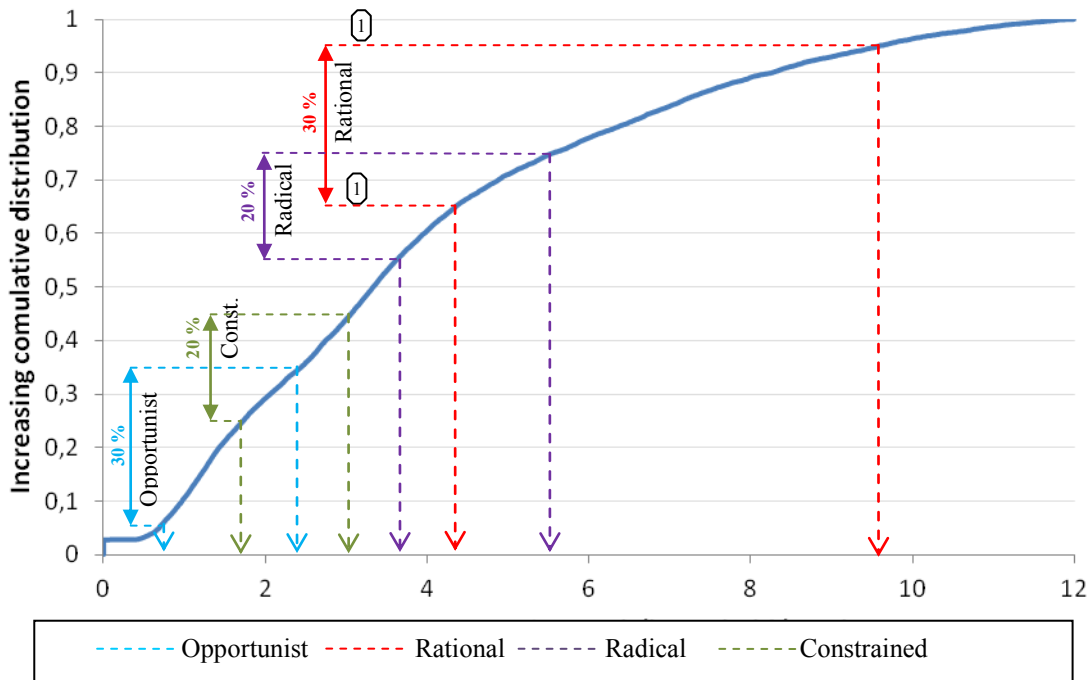


Figure 6.6 : Increasing cumulative distribution of energy consumption for the activity “watching TV”

For example, the rational profile is attributed a ‘++’ indicator for the “watching TV” activity (Table 6.5), meaning that it consumes energy significantly higher than other profiles. Moreover, the size of the rational profile in the total population is 30%. Therefore, we can project the profile size on the cumulative graph in Figure 6.6 as follows: (a) the interval is centered at 80%, which is a value that we supposed for the ‘++’ indicator to represent its high consumption profile (b) the interval is located thus between 65% and 95% (lines numbered ‘1’). Consequently, the energy consumption interval for the rational profile can be deduced by projecting lines numbered ‘1’ on the x-axis (Figure 6.6). This interval is thus of between 4.2 and 9.5 KWh/household/week. The same procedure is done for other profiles and the results are illustrated in Table 6.8.

Table 6.8: Estimating energy consumption intervals for each archetype persona using quantitative results

	Opportunist	Rational	Radical	Constrained
Indicator	--	++	+	-
% of the population (from Table 6.7)	30 %	30 %	20 %	20 %
Center of the interval on the cumulative curve at %	20 %	80 %	65 %	35 %
Consumption interval (KWh/week)	[0.8, 2.5]	[4.2, 9.5]	[3.7, 5.5]	[1.8, 3]

Having these results in Table 6.8, the relative difference of energy consumption between each energy-related profile from one side and the population average profile from the other side can thus be estimated. The results are shown Table 6.9. For instance, the energy consumption of the radical profile for the “watching TV” activity ranges between 3.7 and 5.5 KWh/month. The mean consumption of the total population is equal to 3.95 KWh/household/week (chapter 4). Hence the relative difference for the radical profile ranges between -6% and +39% from the average population consumption value (Table 6.9).

Table 6.9: Relative difference of energy consumption from the average

	Opportunist	Rational	Radical	Constrained
Consumption interval for each profile (KWh/week)	[0.8, 2.5]	[4.2, 9.5]	[3.7, 5.5]	[1.8, 3]
Relative difference from population average value	[-80%, -37%]	[+6%,+141%]	[-6%, +39%]	[-54%, -24%]

The results in Table 6.9 reveal that households of rational profile are the highest consumers where their energy consumption may reach 141% more than the average of the population. Radicals are thus in the second place, followed by constrained households and finally opportunists. The preceding results show therefore how qualitative socio-behavioral approaches can be coupled with quantitative modeling approaches in order to predict energy consumption behaviors in residential buildings. The relative difference of energy consumption among the four socio-behavioral profiles and their dispersion from the average of the population may be of high interest. For instance, in the case where building constructors have an idea about the socio-behavioral characteristics of future occupants, they can get a picture about their possible energy consumption profiles.

6.3 Integrating the proposed modeling approach into the industrial context of residential buildings

Building occupants constitute a primordial part of the whole building’s life cycle. Their living pattern and energy consumption trends are major determinants of a building performance during the use phase. For these reasons, building constructors nowadays pay a special attention to predict future impact of occupants on the overall performance of a building, as early as possible in the design phase. This attention is even more substantial for the case of energy-efficient buildings as we have seen in chapter 1. For this reason, they devote considerable effort to finding tools, techniques and approaches that will enable them to better

understand, model and predict more accurately the energy consumption yielded by future occupants.

A well-known French construction enterprise, which is a partner of our research work, emphasizes the need for modeling and simulating approaches similar to the one presented in this thesis. In what follows, we summarize the different possibilities of how our model might be integrated into the industrial context and what its future possible applications can be.


6.3.1 Integrating the modeling approach into the design process of residential buildings


Following the discussions with engineers, designers, and technical directors from the construction enterprise partner of this research work, a number of possible future use cases of the model are identified. In this section, we demonstrate these use cases and discuss their advantages in buildings' industrial context.


First of all, we recall here that the SABEC model is implemented through simple interfaces on a Microsoft Excel work book. The statistical data used and the calculation mechanisms are included to provide a simulation for specific households. The Excel work book may be user-configured or incorporated into other models as required. In addition, for the sake of creating very large data sets and to reduce calculation time-cost, the model was implemented in Python language. A graphical user-friendly interface is developed on a host website to facilitate the usage and the communication of model functionalities. Some screenshots of this interface are shown in Figure 6.7 and Figure 6.8.

SABEC Model

Stochastic Activity-Based Energy Consumption Model







by Toufic ZARAKET

1. Calculation Type

Calculation Type	Activity	Save Excel Results
<div style="border: 1px solid #ccc; padding: 2px;">Random Households</div> <div style="border: 1px solid #ccc; padding: 2px; background-color: #e0e0e0;">Specific Household</div> <div style="border: 1px solid #ccc; padding: 2px; background-color: #e0e0e0;">Random Households</div> <div style="border: 1px solid #ccc; padding: 2px;">Comparison between random HHs with additional constraints</div>	<div style="border: 1px solid #ccc; padding: 2px;">Laundry</div>	<div style="border: 1px solid #ccc; padding: 2px;">yes</div>

2. Household Attribute Constraints

<input checked="" type="checkbox"/> Given HH Type	<input type="checkbox"/> Given Nb Adults	<input checked="" type="checkbox"/> Given Nb Children	<input checked="" type="checkbox"/> Given Total Income Range	<input type="checkbox"/> Given Env. Awareness Attr.
---	--	---	--	---

Household Type	Number of Children	Total Income
<div style="border: 1px solid #ccc; padding: 2px;">Couple with one or more chi</div>	<div style="border: 1px solid #ccc; padding: 2px;">[1, 2]</div>	<div style="border: 1px solid #ccc; padding: 2px;">[3000,4000] EUR</div>

Choosing simulation/calculation type

2. Household Composition

Number of Adults	Number of Children
<div style="border: 1px solid #ccc; padding: 2px;">2</div>	<div style="border: 1px solid #ccc; padding: 2px;">0</div>

2.1.1 Adult No.1 Individual Properties

Age	Gender	Monthly Income	Activity Status
<div style="border: 1px solid #ccc; padding: 2px;">30 years</div>	<div style="border: 1px solid #ccc; padding: 2px;">Male</div>	<div style="border: 1px solid #ccc; padding: 2px;">2500 EUR</div>	<div style="border: 1px solid #ccc; padding: 2px;">Active employed</div>
CSP	Education Level		
<div style="border: 1px solid #ccc; padding: 2px;">Independant</div>	<div style="border: 1px solid #ccc; padding: 2px;">No diploma or CEP</div>		

2.1.2 Adult No.2 Individual Properties

Age	Gender	Monthly Income	Activity Status
<div style="border: 1px solid #ccc; padding: 2px;">30 years</div>	<div style="border: 1px solid #ccc; padding: 2px;">Male</div>	<div style="border: 1px solid #ccc; padding: 2px;">2500 EUR</div>	<div style="border: 1px solid #ccc; padding: 2px;">Active employed</div>
CSP	Education Level		
<div style="border: 1px solid #ccc; padding: 2px;">Independant</div>	<div style="border: 1px solid #ccc; padding: 2px;">No diploma or CEP</div>		

Defining input parameters for specific households

Figure 6.7 : Screenshots from the graphic interface of SABEC model

BY TOUFIK ZARAKET

1. Calculation Type

Calculation Type:
 Activity:
 Save Excel Results:

2. Household Attribute Constraints

Given HH Type
 Given Nb Adults
 Given Nb Children
 Given Total Income Range
 Given Env. Awareness Range

Given Ref. Person Attr.

Household Type:
 Number of Children:
 Total Income:

3. Reference Person Attribute Constraints

Age range
 Gender
 Income range
 Activity Status
 CSP

Education level

Age:
 Gender:
 Monthly Income:
 Activity Status:

Defining constraints on input variables

Mean Consumptions and Service Units

Energy Cons. Total <input type="text" value="12.3816"/> KWh/month	Energy Cons. Clothes <input type="text" value="8.7023"/> KWh/month	Energy Cons. Linens <input type="text" value="3.6793"/> KWh/month	Water Cons. Total <input type="text" value="1.0253E3"/> L/month	Water Cons. Clothes <input type="text" value="741.1272"/> L/month
Water Cons. Linens <input type="text" value="284.2151"/> L/month	Total Nb. cycles <input type="text" value="14.5426"/> cycles	Clothes Washing Cycles <input type="text" value="10.5664"/> cycles	Linen Washing Cycles <input type="text" value="3.9762"/> cycles	

Energy Consumption spectrum, Cumulative distribution function (KWh/month)

[Download 3_24_Graph_4.png](#)

Sample of simulation results

Figure 6.8: Screenshots from the graphic interface of SABEC model (continued)

The development of this tool aimed at communicating the results of our research work to collaborators from the industrial sector. Its functionalities are still yet limited to simulate the two domestic activities treated in this thesis. In future work, the tool can be developed in collaboration with computer programmers and developers so that it can serve as a professional tool for building experts.

6.3.1.1 Using the model for more accurate forecasting of occupant-related energy consumption

During the design phase of buildings, designers and experts rely on simulation tools for assessing and predicting future energy performance of buildings. These energy simulation tools, such as EnergyPlus, eQUEST, ESP-r and TRNSYS, predict the energy performance of any building to be constructed. In general, such tools support the understanding of how a given building operates according to certain criteria and enable comparisons of different design alternatives. However as discussed in the literature review, limitations apply to almost every available tool of this kind today. This is because simulation tools focus primarily on the structural behavior of buildings and their relations to specific environmental conditions while taking insufficiently into account the role of the occupants. Typically in building simulators, only the thermal heat generated by appliances and occupants is considered. Moreover, the occupants are considered only as being present or absent without taking into account the way they behave to consume energy. This simplification of occupants' behavior and energy consumption patterns leads eventually to unreliable energy estimates, and results thus in variations between predicted and real energy performance (refer to chapters 1 and 2).

The stochastic activity-based approach presented in this thesis can thus be used as a complementary tool to traditional building simulators in assessing energy consumption of residential buildings¹⁴. The advantage of the generalized SABEC model is that it can provide detailed occupant-related energy consumption values per given household and per domestic activity. The results of the SABEC model can then be combined to building simulators estimations so that to have a better picture of energy consumption. This coupling of SABEC model with energy simulation tools can thus reduce uncertainties while forecasting energy performance of buildings and consequently making predictions more accurate.

¹⁴ This issue was discussed in detail in chapters 1 and 2.

6.3.1.2 For promoting design and construction solutions

It is obvious that a better modeling of the energy demand of building's future occupants' can result in better energy performance estimations, and thus may guide some design solutions. If building constructors possess the full picture of energy consumption patterns at the occupant level, they might promote design and technical solutions for limiting the energy consumption of some end-uses by making them more independent of occupants' variability. For example, the installation of energy-efficient bulbs in the dwellings can reduce the energy consumption of lighting, and limit thus the consumption variability that may arise from occupants' personal lighting equipments. A number of other examples can be given here, however in this section we will handle a single example related to the energy consumption due to the laundry activity.

6.3.1.2.1 The example of laundry room with energy-efficient washing machines

As discussed previously in chapter 5, doing laundry at home is considered as a major domestic activity. The washing machine is a commonly used device which is possessed by almost 95% of French households. This high ownership rate is accompanied with an extensive use of washing machines and thus high levels of energy and water consumption. According to some French studies, a washing machine consumes an average of 169 kWh per year and representing thus about 7% of households' total electricity consumption, where in some cases the consumption of washing machines can reach four or five times the average value. In this section, we perform a simple study to examine the advantages of the following specific design/construction alternative: What if the enterprise decides to equip the building with a central laundry room provided with energy-efficient washing machines only?

It must be accentuated here that we do not perform a complete study to examine thoroughly neither the costs for constructing such laundry room and for buying machines, nor the willingness of future occupants to do their laundry in this central room rather than using their own appliances. We aim only at evaluating the possible benefit, on the energy consumption balance, resulting from this proposed design alternative.

The design alternative concerning the activity "washing laundry" is taken as follows: For a newly constructed building composed of 54 dwellings of different sizes, the constructor installs a laundry room with washing machines of energy rating A+++ (energy consumption= [0.11- 0.13] kWh/Kg, water consumption = 7 liters/Kg) and having each a drum capacity of

10 Kg. In this case we suppose that the occupants will use this laundry room to do their laundry instead of using their own washing machines.

Using our simulation model, we perform two estimations of energy and water consumption for the “washing laundry” activity as follows:

- First case:** this case corresponds to the absence of a central room in the building. Thus we consider that households will do their laundry at home. The simulations are performed as seen earlier in chapter five where each household is attributed a washing machine randomly according to its socio-demographic and economic attributes.
- Second case:** The constructor installs a central laundry room in the buildings, and the occupants will wash their laundry in this central room (using the energy-efficient machines).

The simulation is performed in a way that, when a household is generated randomly by the model, the energy consumption used for doing laundry by this same household is estimated for both cases above (keeping the same characteristics of the household, but changing only the characteristics of the washing machine). A number of 10000 simulations are performed, and then 54 dwellings are drawn randomly for both cases (same households for the two cases). The electricity and water consumption results for the 54 households are represented through Figure 6.9 and Figure 6.10 respectively.

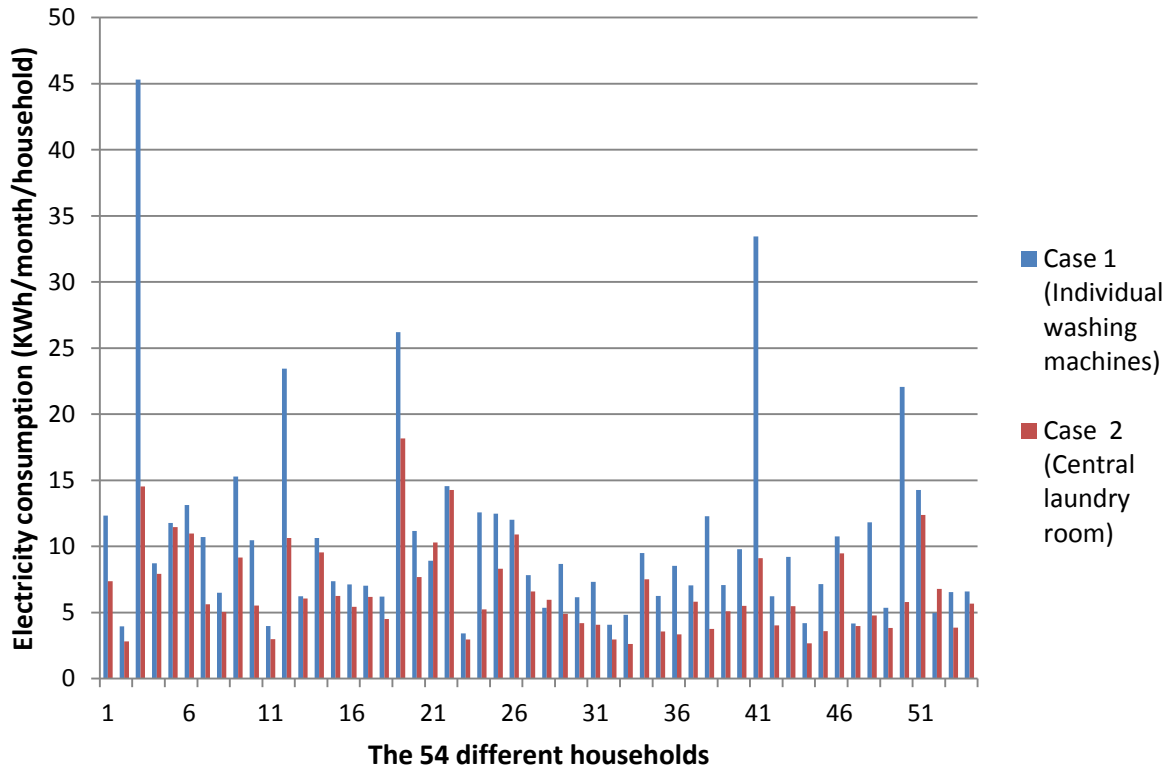


Figure 6.9 : Electricity consumption results for each household according to both cases

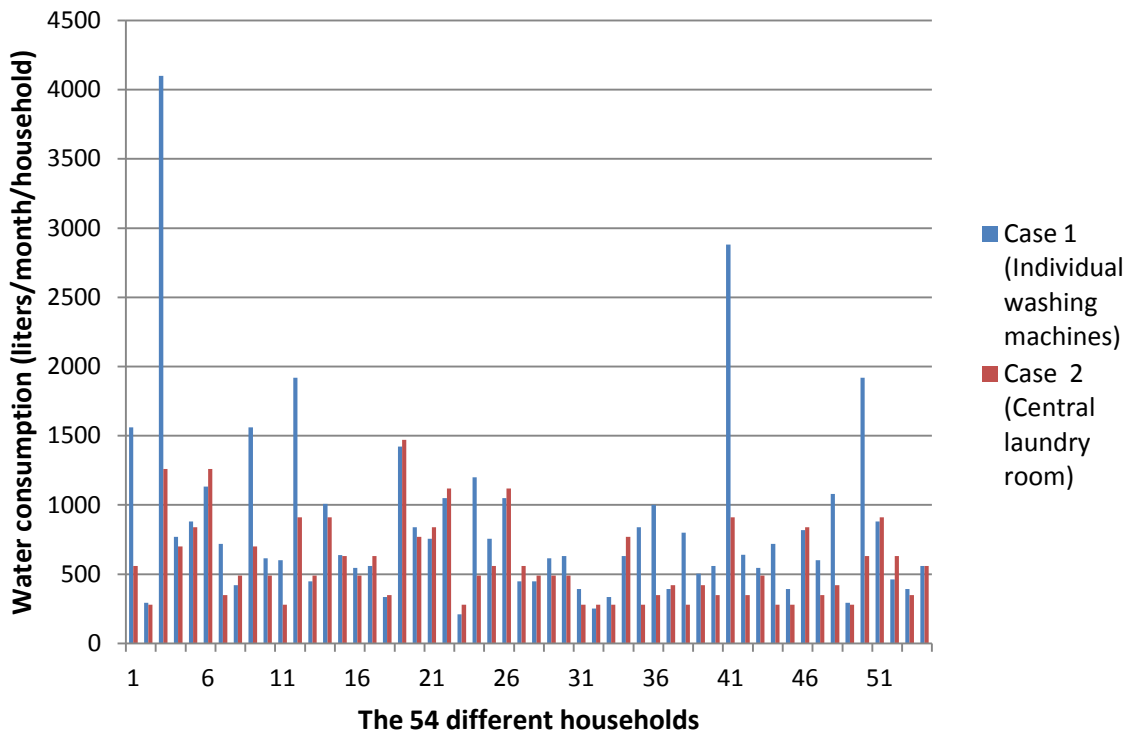


Figure 6.10 : Water consumption results for each household according to both cases

The detailed descriptive statistics of consumption results for both cases are illustrated in Table 6.10. It can be noticed that the average electricity consumption per household for case 1 is equal to 10.42 KWh/household/month which is 58% higher than that of case 2 which is equal to 6.62. As for water consumption, its average is 841 liters/month for case 1 which is 45% more than the average for case 2. This difference in consumption levels is valid also at the scale of the building that is for the whole 54 households.

Table 6.10: Comparison between consumption results for both cases

	Electricity (KWh/month)		Water (liters per month)	
	Mean per household	Total for 54 households	Mean per household	Total for 54 households
Case 1	10.42	563	841	45429
Case 2	6.62	357	579	31290
Savings if case 2 applied		206 (37%)		14139 (31%)

A simple comparison between simulation results for both cases reveals that case 2 may save a significant amount of energy. The savings of electricity for all 54 households can reach 206 KWh/month which represents a reduction of 37%. Moreover, the savings of water are about 14139 liters/month that is a reduction of 31%.

The preceding simplified example demonstrates the possible usage of the probabilistic activity based approach. By defining certain design and construction solutions, constructors may be capable of evaluating energy and water consumption savings at the level of the households as well as at the level of the whole building.

6.3.2 For offering and improving services and promoting eco-innovations

To keep pace with the evolution of building regulations and to better design their future buildings, construction firms started making use of new eco-innovations. For instance, our partner construction enterprise has started installing connected tools for the newly constructed green buildings (Lemoniteur, 2011). These tools are in fact touch screen tablets which display consumption of space heating, hot water and electricity for each dwelling (

Figure 6.11). The installation of these instruments is included in a global offer which also involves technical maintenance of the building for several years. The tablets can be enriched by a range of services (e.g. weather forecasts, local public transport timetables), depending on the needs and demands of tenants and landlords.

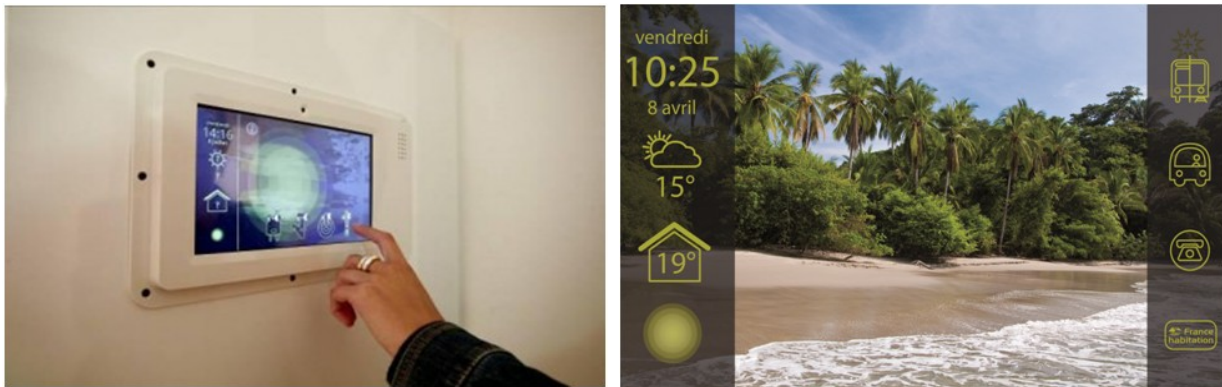


Figure 6.11 : Smart tablets used for measuring and monitoring domestic energy consumption (Energy Pass in (Lemoniteur, 2011))

These tablets are used for two main objectives: (1) to provide real-time information for occupants about their energy consumption levels (heating and hot water) and (2) to supply building owners and constructors with large data sets of energy consumption. It should be noted, however, that such tools do not provide till now detailed consumption information per end-use. Occupants are only informed about their temperature setting-point and their hot water consumption through a simple graphic interface (Smileys).

Given the aforementioned, the proposed activity-based model can thus be possibly used in order to enrich such smart tools. For instance, if major energy consuming end-uses are identified, building experts can install additional intelligent sensors to measure and monitor these consumptions. Moreover, occupants may have more detailed picture about their electricity and water consumption per each domestic activity and thus can be incited to limit this consumption.

On the other hand, through such connected tools, constructors will be provided with relevant and detailed information about energy and water consumption during the use phase the building. Consequently, they may use these information to improve the design of new buildings, by better adapting them to users' needs and by providing alternative services and design solutions.

6.3.3 Integrating the modeling approach into the marketing process of residential buildings

6.3.3.1 For targeting clients and adapting building designs

Building constructors and owners define a set of design specifications for each of their buildings. They modify these specifications according to the type of the building, the residential zone, and the socio-economic characteristics of its future users. This is achieved by relying on their past experience or on information coming from surveys conducted in the residential zone. It may be said that a customer segment is targeted. Normally, it is uncommon for building owners and constructors to possess accurate and exhaustive information about future occupants' socio-demographics prior to buildings' use phase. Nonetheless, they may acquire a rough picture of these characteristics through the abovementioned surveys. We may thus postulate that this information could be used at best to adapt the design of buildings so that they conform to the expected life style and consumption behaviors of future occupants.

If this information is integrated into the probabilistic approach proposed in the thesis, more precise predictions of energy consumption can be established. For instance, information about future users can be used to depict the social profiles for which they belong, which is different from the national household distribution, and hence deduce their consumption patterns. Therefore, a more precise picture can be drawn about the future performance of a building under particular specifications. Consequently, the latter may be modified in order to (1) better correspond to future occupants' life style and consumption behaviors, or (2) reduce the possible variability (standard deviation) of energy and water consumption for potential household types and then design robust dwellings.

6.3.3.2 For refining energy performance guarantees

The tendency towards constructing low-consuming and nearly zero-energy buildings is pushing the design phase to become more and more sensitive to consumption characteristics. Moreover, a so called “energy performance contract”¹⁵, which is a performance commitment between building constructors and owners, is a new market expectation emerging in France. By this contract, constructors commit to deliver an eco-efficient building and to guarantee this performance threshold for a certain number of years after handover. In case if energy

¹⁵ In French : Contrat de performance énergétique (CPE)

consumption thresholds defined in the contract are surpassed during the use-phase of the building, the constructor is committed to pay a penalty for the sake of the owner. For this reason, building constructors devote considerable effort to finding tools, techniques and approaches that will enable them to better understand and interpret complex usage phenomena of buildings, and consequently to refine the proposal of energy performance contract.

The construction enterprise partner of our research work is a pioneer in offering such energy performance contracts in France. Experts from this company emphasize the high influence of occupants' behavior on the variability between predicted and real energy consumption. They confirm that a better modeling of households' energy consumption with a more accurate estimation could be very beneficial for defining consumption thresholds of the performance contract. Therefore, our modeling approach can be used in this scope. In addition, the probabilistic nature of SABEC model's results can give a more precise image of energy consumption intervals (minimum and maximum consumption) per activity and per household (refer to chapters 4 and 5). Accordingly, the proposed modeling approach, coupled to traditionally used energy simulators, may guide in refining such energy performance guarantees as a function of future occupants' profiles.

6.4 Conclusions

In this chapter, various issues are tackled for generalizing the modeling and simulation method and making it practically usable in a professional context. We first discuss the applicability of the SABEC model on the different domestic energy end-uses and then a generalization approach is proposed. The generalized structure of the model together with its different objects is illustrated discussed. Second, we examine how the model can be simplified so that to reduce its complexity. For this sake, a variance-based sensitivity analysis on the model for "washing laundry" activity is performed and major input variables are identified. The three most influencing factors for this activity are found to be the number of adults, number of children and household's income. Then, a simplification example is demonstrated based on these variables. A comparison between simulation results from both simplified and refined model is performed and discussed. Third, we expose socio-behavioral approaches for modeling domestic energy and we discuss the possibility and interest of coupling qualitative social models with quantitative approaches such as that proposed in this thesis. Fourth, we summarize the different possibilities of how our model might be integrated

into design context of buildings and its future possible applications. A case study on the installation of central laundry room into buildings is presented. Simulation results of energy consumptions for this case study are presented and discussed. Other possible applications of the model are also sketched and illustrated through examples.

General Conclusions

The general conclusions of this dissertation are divided into three sections. The first section provides a summary of our scientific contributions along the present dissertation. These contributions are expressed in a way to provide responses to the three research questions of this work. The second part of the conclusions summarizes the limitations of the present work. The third part exposes the perspectives issued out of this dissertation.

Contributions

Response to Question 1

Is it possible to depict, characterize and model energy consumption in residential buildings through an activity-based approach?

Energy use in residential buildings is embedded in most aspects of occupants' daily life. People use energy to satisfy certain daily living activities such as preserving and preparing food, supplying heat and light, and maintaining comfort and sanitation. Apart from building's inherent systems (HVAC and lighting), domestic appliances used by occupants constitute the major part of residential energy consumption. These devices are used by households for performing daily living activities such as washing, cooking, entertaining, and others. Therefore, the best way for modeling energy consumption of home appliances and their corresponding use patterns by occupants, is to take domestic activities as starting point.

In the present research work, we introduced a systematic breakdown structure of residential energy consumption per activity. Domestic energy consuming activities are then identified together with their corresponding impact on building's energy performance balance. An activity-based approach is thus adopted for modeling occupant-related energy consumption. A classification of activities into shared and additive types is introduced to represent activity patterns. This classification enables assessing realistic energy consumption behavior of occupants. In order to quantify a given activity, the notion of "activity's service unit" is introduced. Service units give a description of activity quantities, and consequently energy demand, at both individual and household levels. Activity's service units can then be associated to the usage of one or more domestic appliances in order to predict energy

consumption. The proposed activity-based approach can account for dependencies between service units of different activities. This is an important feature for modeling the total energy consumption yielded by whole domestic activities.

Response to Question 2

How to model and simulate energy consumption in residential buildings while accounting for the variability of household profiles as well as the stochastic nature of domestic activities and equipment possession?

Energy consumption can vary dramatically between different households. This variation is due to the diversity of occupant profiles and their corresponding consumption figures. In order to account for this variability, a number of points are considered in the present research work.

First, the proposed modeling approach considers a sufficient number of attributes for representing households' and individuals' profiles. Variables characterizing the social, demographic, economic, and behavioral attributes of households' are considered. Second, the proposed model establishes probabilistic relations between occupants' attributes (family type, income, etc.) from one side, and the corresponding appliance ownership rates, appliance characteristics and power rating, and activity quantities from the other side. These relations are constructed based on real statistically derived distributions. Through these probabilistic relations, activity quantities are determined as a function of households' attributes, and are then translated into energy consumption values. These consumption predictions are yielded in the form of probabilistic spectrums revealing thus consumption variability per each household profile and each domestic activity.

Therefore, the main advantages of the above-described model are thus its capability to provide accurate energy demand estimates per household and per activity, and to reveal variability in consumption values among different households. The proposed SABEC model provides three main functionalities by calculating energy consumption (1) for a specific household (2) for a cluster of households having common input attribute(s) to study variability among them and (3) for a random population of households to have a representation of the whole population.

Responses to Question 3

Is it possible to integrate “energy consumption models per household profile” into the design process of buildings, and how such models can be used in the perspective of improving the robustness of building’s energy performance?

Building and energy experts manifest their need to powerful simulation tools capable of providing accurate energy demand estimations. Such tools are highly required especially for the case of green buildings where the impact of occupants on the energy performance is very substantial. The proposed modeling approach in this thesis falls directly into these objectives. A part of this dissertation was devoted to expose the different possibilities of how our model might be integrated into design context of buildings and what its future possible applications could be.

The proposed model can be used as a complementary tool to traditionally adopted energy simulation tools. It can provide more accurate forecasting of occupant-related energy consumption per household and per domestic activity. These precise energy predictions can thus be used to guide the refining of energy performance guarantees by defining more accurate consumption thresholds. In addition, the model can be used to test design alternatives which are highly occupant-dependent (example of laundry room with energy efficient washing machines).

The proposed activity-based model can also be possibly used in order to enrich smart tools used for monitoring residential energy consumption. For instance, if major energy consuming end uses are identified, building experts can install additional intelligent sensors to measure and monitor these consumptions. Moreover, occupants may have more detailed picture about their electricity and water consumption per each domestic activity and thus can be incited to limit this consumption. On the other hand, through such connected tools, constructors will be provided with relevant and detailed information about energy and water consumption during the use phase of the building. Consequently, they may use this information to improve the design of new buildings, by better adapting them to users’ needs and by providing alternative services and design solutions.

Limitations

The limitations of the present work are the following:

- The proposed approach is limited to modeling energy consumption of domestic activities. It does not provide total energy estimates of dwellings (end uses related to buildings' inherent systems, such as lighting and heating, are not considered)
- The modeling approach was applied on two domestic activities only. For the instant, it cannot provide the full picture of occupants' activity-related energy consumption.
- The proposed stochastic model is based on statistically-derived data. Data concerning some model variables were not available, and were thus replaced by data collected from small scale surveys which are less reliable.

Future work

In this research work, we present a methodology to generate energy demand estimates as a function of individuals' and buildings' activities. The proposed model can be applied as a complement tool for industrial energy simulation systems. To achieve this perspective, some possible directions in which this work can be extended are:-

- Extend the application of the modeling approach to other domestic activities.
- Simplification of the model to optimize its time and computational costs while maintaining a good output quality. This can be done by reducing model variables as it was done for the “washing laundry” activity.
- Once the model is simplified and generalized to all other domestic activities, it can be developed into a simulation tool. This tool can be later industrialized and integrated into the design process of buildings.

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Appendix A: Web survey for assessing household patterns of washing laundry at home

Statistical data concerning the trends of washing laundry in French households is rarely available. The studies that we found in literature review do not give insights about a number important aspects related to households behavior towards doing laundry at home. For this reason, we conducted a web-based survey in order to deepen our knowledge about the patterns/trends adopted by French households for doing the "Washing laundry" activity.

The purpose of this web-based survey is to collect information on the types and characteristics of cloth washers present within French households and the way in which household members do their laundry at home. It also provides us with a comprehensive knowledge about the variability in consumer behavior related to the activity "washing clothes" among different households.

The survey was designed to be short and not time-consuming so that to encourage people for participating. Thus, it was limited to 25 questions and was conducted during September 2013.

The number of respondents, who were invited by email to participate, reached to 105. The participants, as the results show, were from different socio-demographic classes and different household categories. Thus the sample is considered to be sufficiently representative for our scope of work. The detailed results of the survey are presented in this appendix.

Some of the statistical data collected through the survey are used in the model. This is done in order to compensate the lack of nationwide information about laundry activity in French households. Yet, surveys with larger samples are still needed to validate these statistical data used in the model.

Questions concerning the composition of your household

Q.1. What type of accommodation / housing you live in?

- Studio
- F1 apartment
- F2 apartment
- F3 apartment
- F4 apartment
- F5 apartment
- Individual home
- Student residence

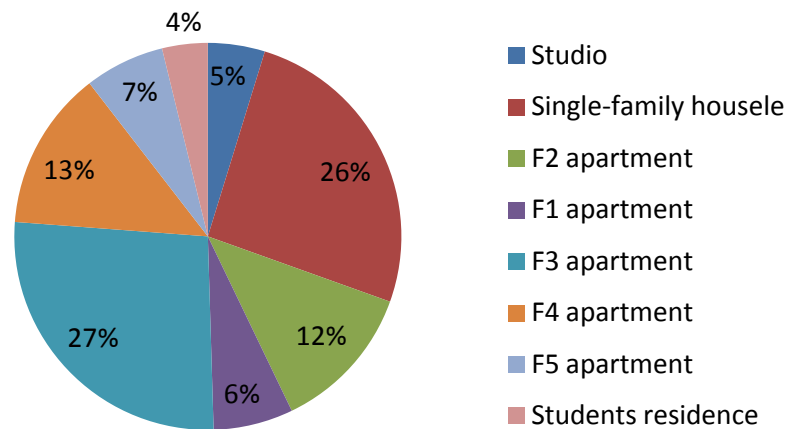


Figure A.1: Survey results for probability distribution of dwelling types

Q.2. Are you?

- Owner
- Tenant

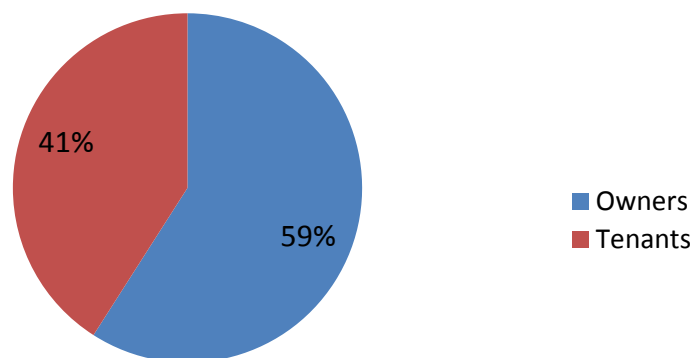


Figure A.2: Survey results for probability distribution of tenure types

Q.3. What is your household type?

- Single
- Couples with children
- Couples without children
- One-parent family
- Others (roommates, etc.)

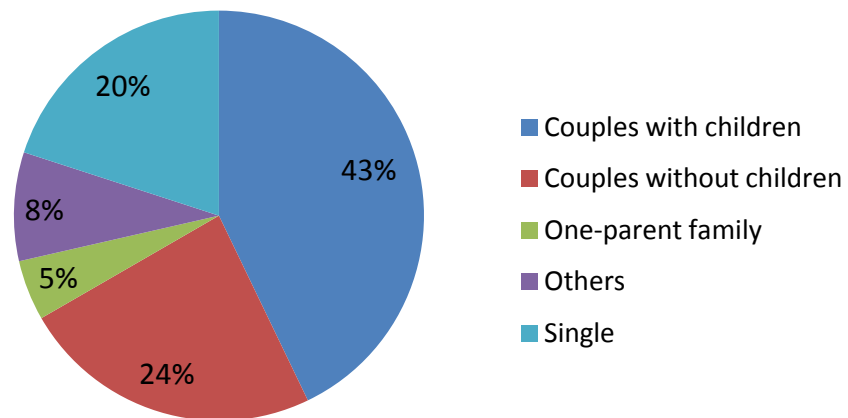


Figure A.3: Survey results for probability distribution of household types

Q.4. How many occupants are there in your household?

- 1
- 2
- 3
- 4
- 5
- 6

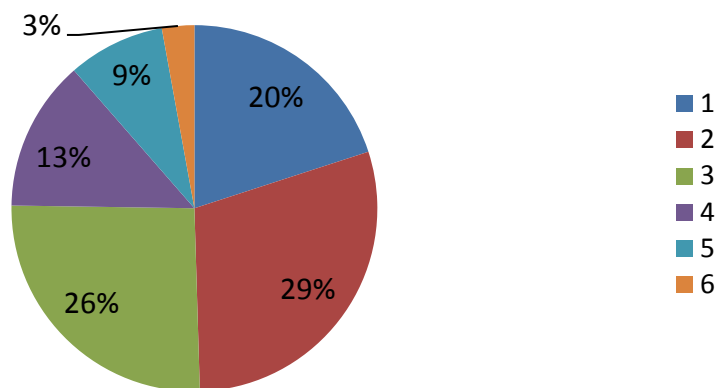


Figure A.4: Survey results for probability distribution of number of occupants per household

Questions regarding the possession and characteristics of your washing machine

Q.5. Is there a washing machine in your home / residence?

- Yes (private machine at home)
- No (no machine in the residence)

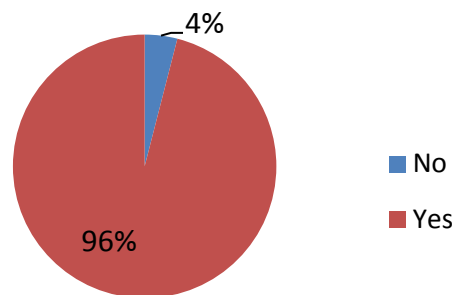


Figure A.5: Survey results for washing machine ownership

Q.6. What is the energy rating for your washing machine?

- A+/A++ (high energy efficiency)
- A
- B
- C
- D
- E
- F
- G (Low energy efficiency)
- I have no idea

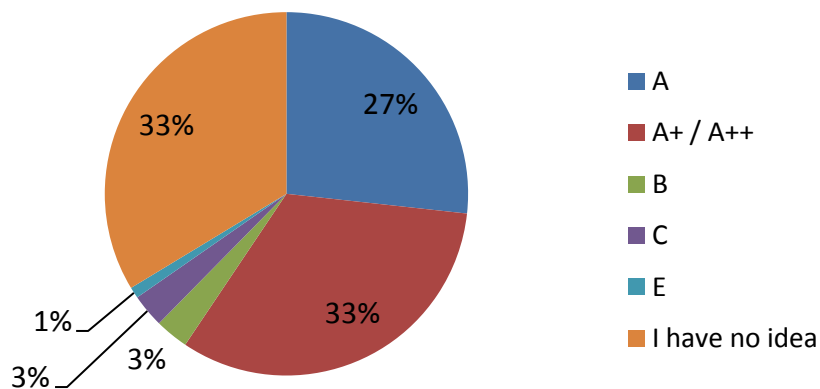


Figure A.6: Survey results for machines' energy rating

Q.7. What is the capacity of your washer?

- 5 Kg
- 6 Kg
- 7 Kg
- 8 Kg
- 9 Kg
- 10 Kg
- >10 Kg
- Other (Specify please)
- I have no idea

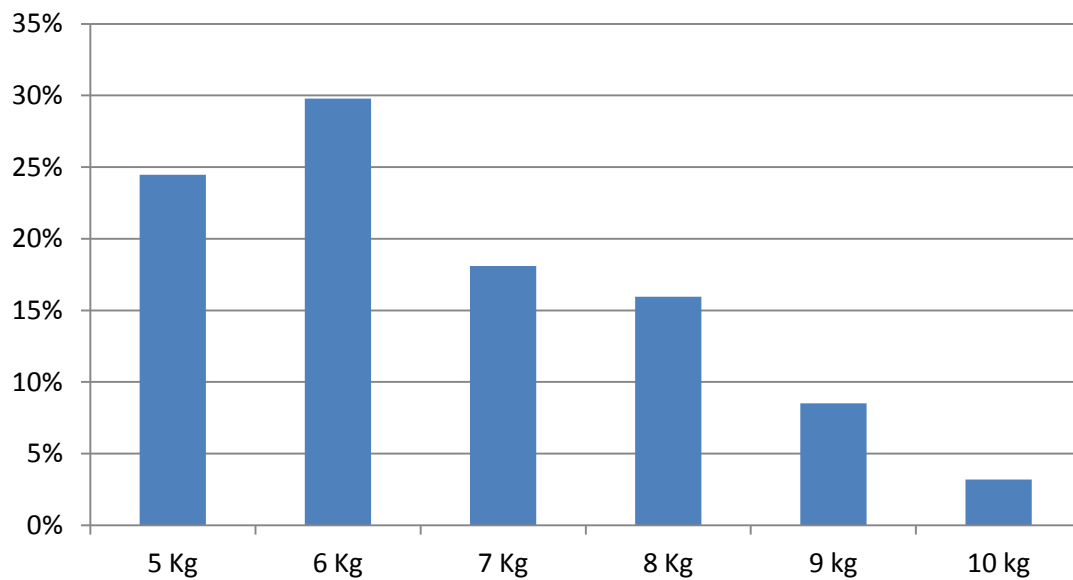


Figure A.7: Survey results for washing machines' capacity

Questions about your habits of "washing laundry"**Q.8 On average, how often do you (adults) put the clothes you wear to dirty laundry?**

- Every day
- Once each 2 days
- Once each 3 days
- Once each 4 days
- Other

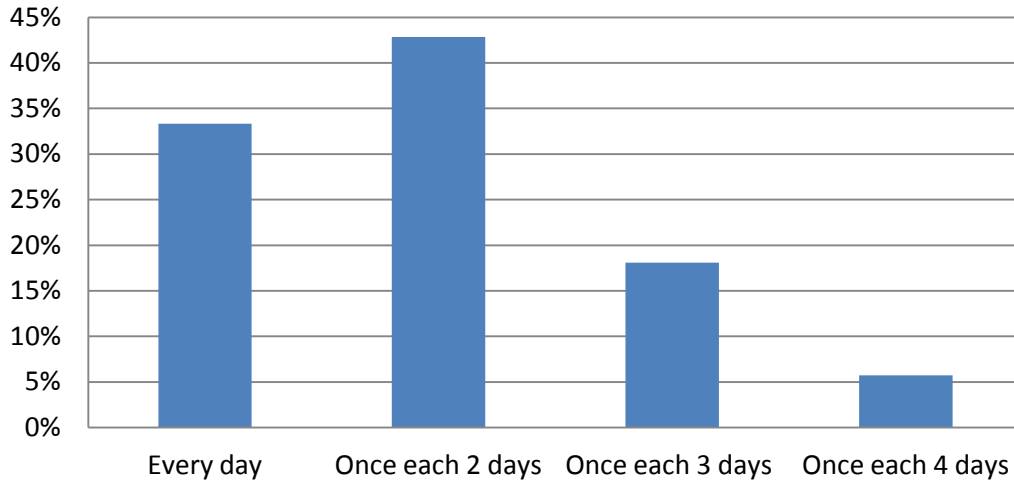


Figure A.8: Survey results for changing clothes frequency (adults)

Q.9 If you have children, how often you put the clothes they wear with dirty laundry?

- Every day
- Once each 2 days
- Once each 3 days
- Once each 4 days
- Other

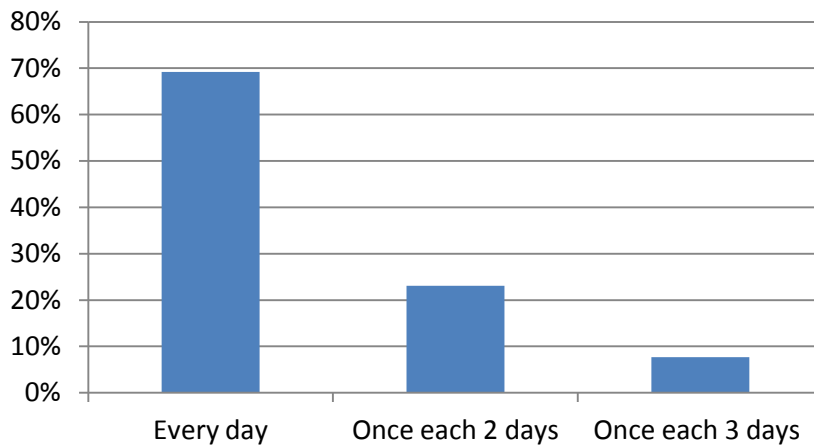


Figure A.9: Survey results for changing clothes frequency (children)

Q10. How do you wash your clothes?

- 100% with the machine
- Machine 90%, hand 10%
- Machine 75%, hand 25%

- Machine 50%, hand 50%
- Machine 25% , hand 75%
- 100% by hand

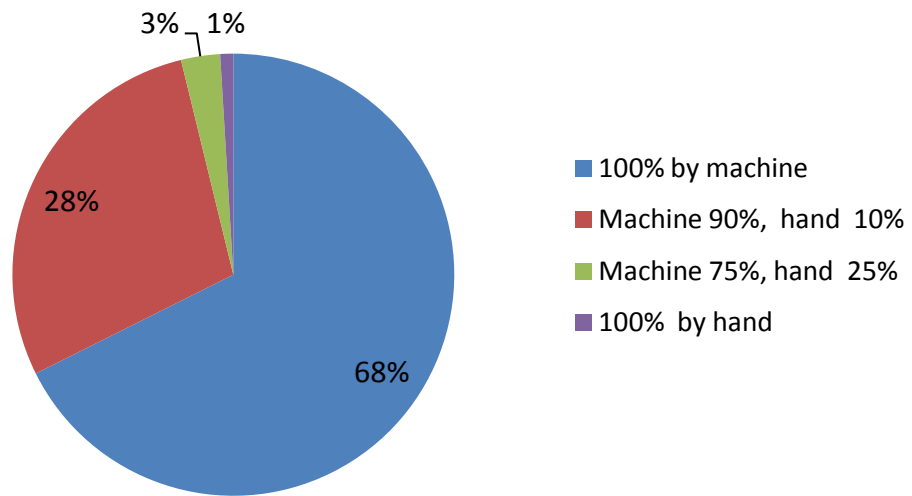


Figure A.10: Survey results for washing laundry method

Q.11. Do you wash your laundry with other occupants of the home (Parents, children, roommates)? or separately?

- Yes, together
- No, we wash our clothes separately

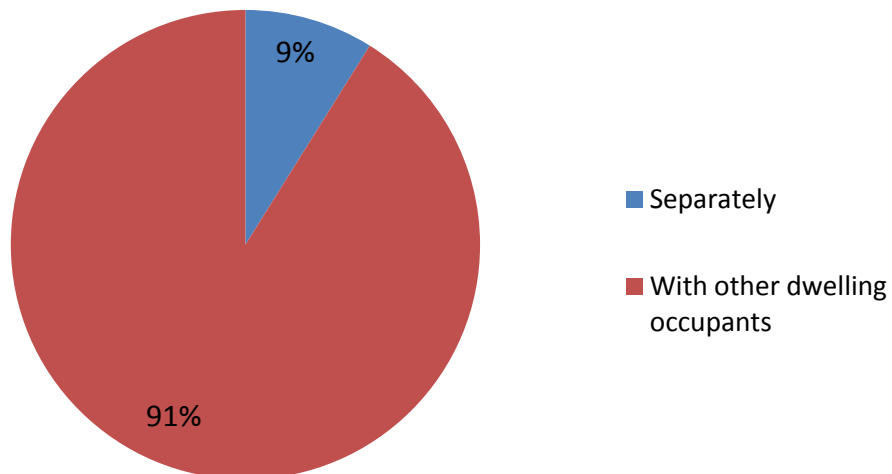


Figure A.11: Survey results for laundry separation per household

Q.12. On average, how many wash cycles do you do per week?

- <1
- 1-2

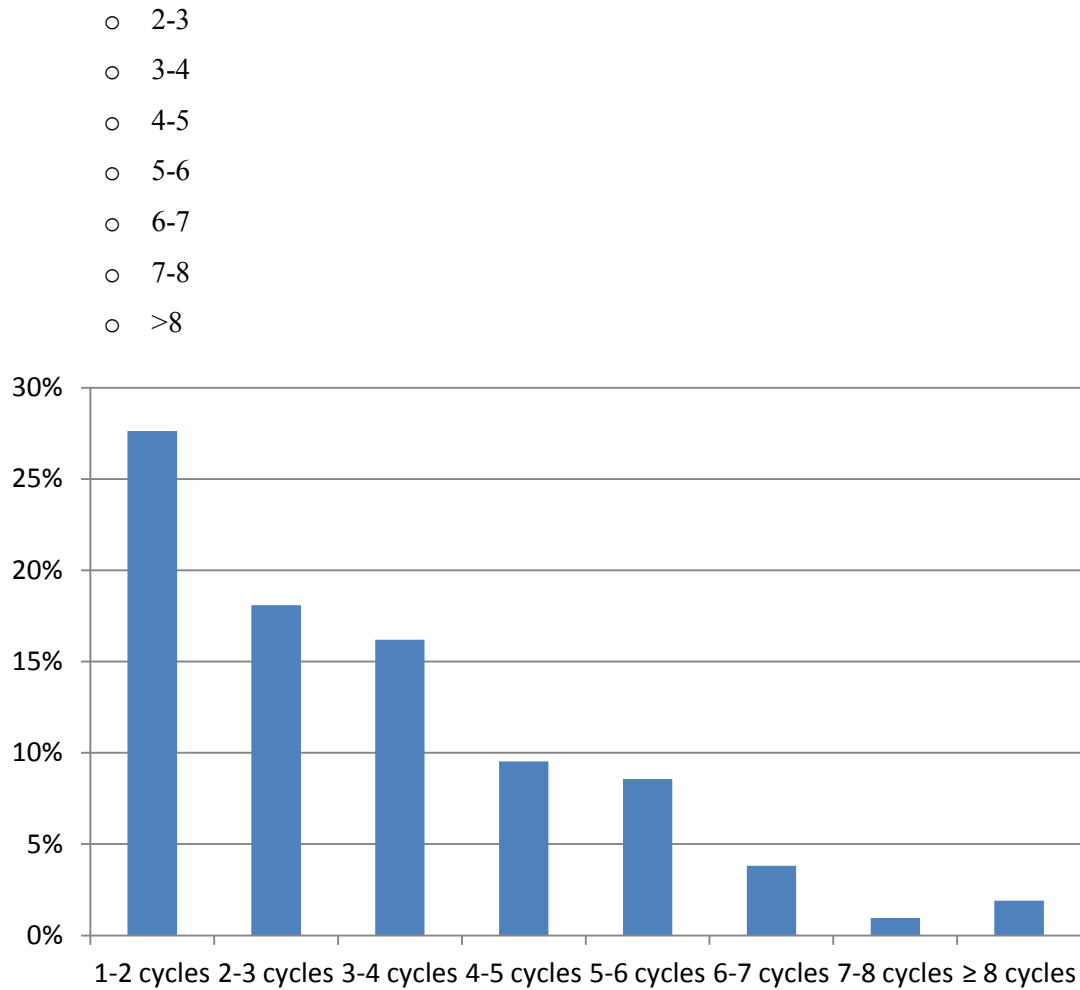


Figure A.12: Survey results for number of washing cycles per week

Q.13. On average, to what percentage you fill the drum of the machine with laundry?

- 10 %
- 20 %
- 30 %
- 40 %
- 50 %
- 60 %
- 70 %
- 80 %
- 90 %
- 100 %

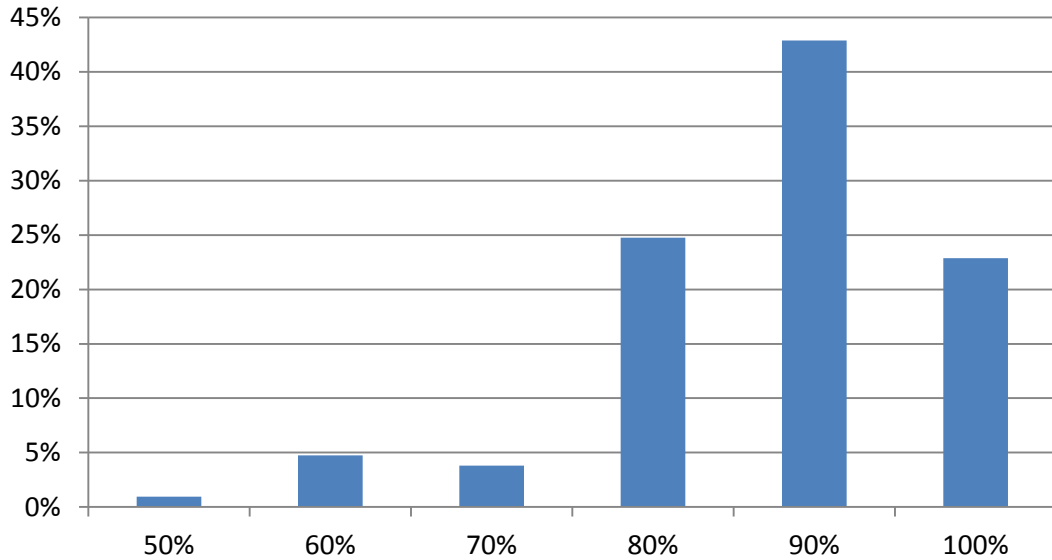


Figure A.13: Survey results for drum filling rate

Q.14. Do you separate your clothes for washing?

- No
- Yes, depending on the type of fabric (cotton, wool, synthetic)
- Yes, depending on the color of the cloth
- Yes, depending on how dirty it is

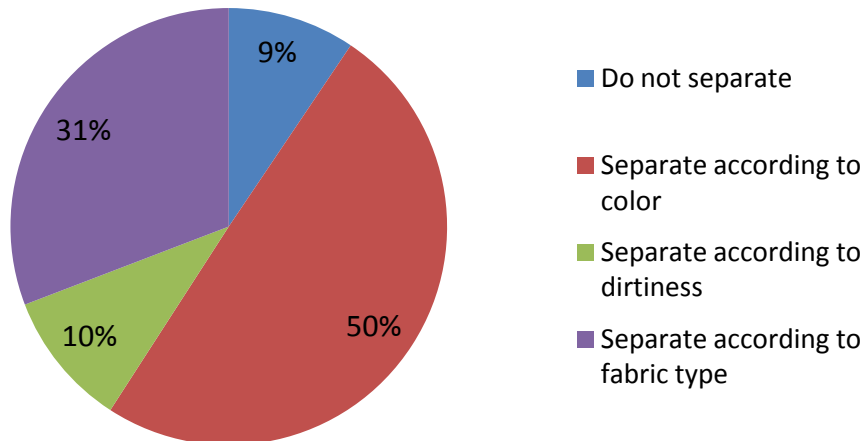


Figure A.14: Survey results for laundry sorting

Q.15. If you separate the laundry according to color, how do you do it?

- White-Colored
- White-Light colored-Dark colored

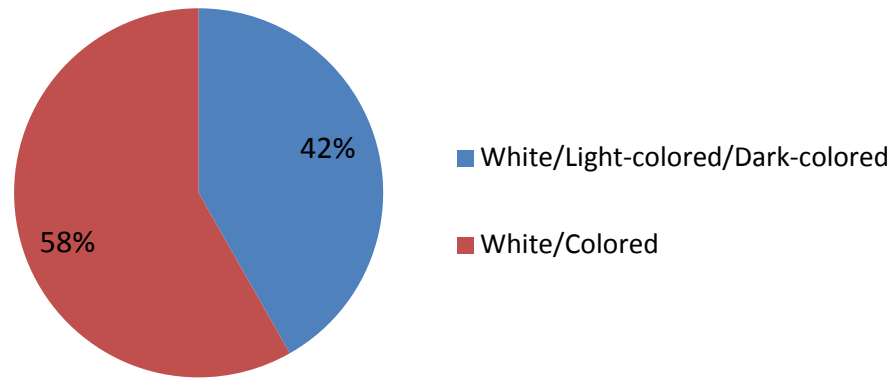


Figure A.15: Survey results for laundry sorting per color

Q.16. On average, what is the proportion of "light-colored" laundry of the total of your laundry?

- 10 %
- 20 %
- 30 %
- 40 %
- 50 %
- 60 %
- 70 %
- 80 %
- 90 %
- 100 %

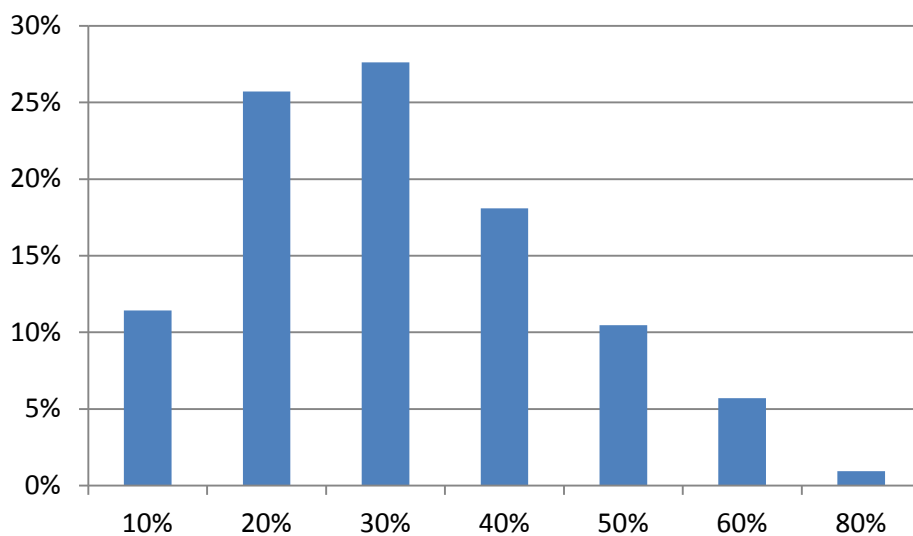


Figure A.16: Survey results for percentage of light-colored laundry

Q.17. In general, what temperature do you use for washing light-colored clothes?

- 30 °C
- 40 °C
- 60 °C
- 90 °C

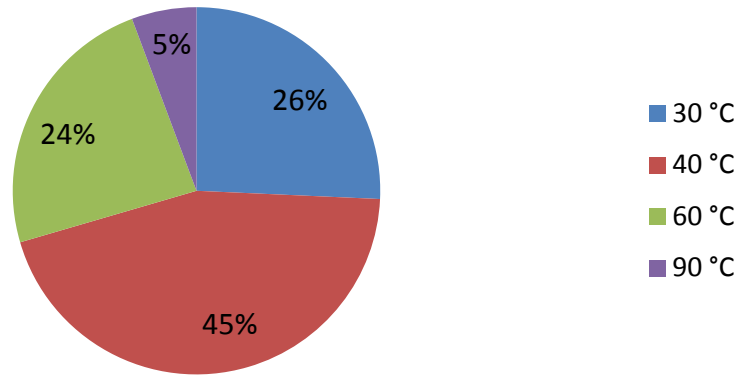


Figure A.17: Survey results for washing temperature of light-colored clothes

Q.18. In general, what temperature do you use for washing dark-colored clothes?

- 30 °C
- 40 °C
- 60 °C
- 90 °C

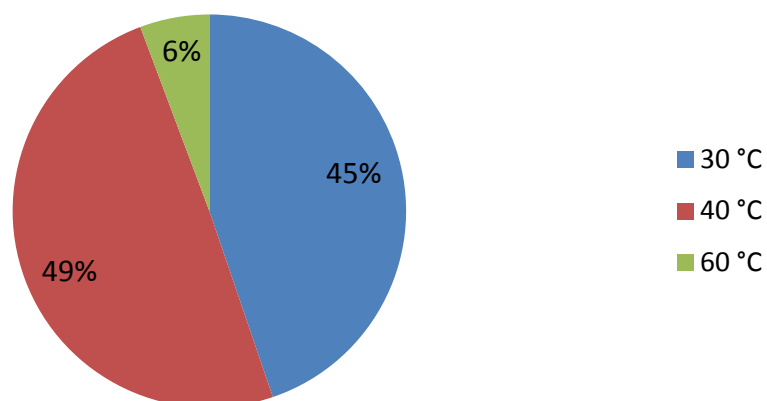


Figure A.18: Survey results for washing temperature of dark-colored clothes

Q.19. In general, what temperature do you use for washing linens laundry (ie: towels, bed sheets, etc..)?

- 30 °C
- 40 °C
- 60 °C
- 90 °C
-

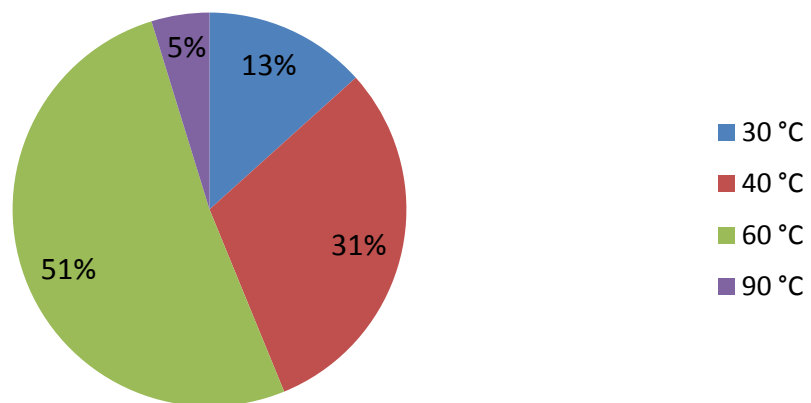


Figure A.19: Survey results for washing temperature of linens

Appendix B: Statistical data of body weight and height of French individuals

Probability distribution of French individuals' body weight as a function of age

A study by Tanguy et al. reveals that the body weight of French individuals follows a normal distribution whose parameters depend essentially on age (Tanguy et al., 2007). Probability distributions for both males and females according to age categories are given in Table B.1. For example, male individuals of 16 years have a mean weight of 64.8 Kg with a standard deviation of 9.6 Kg. Thus, given the age of an individual, it is possible to estimate his/her weight based on the corresponding normal distribution.

Table B.1: Normal probability distributions of body weights according to age (Tanguy et al., 2007)

Age	Normal law parameters $N(\mu, \sigma)$			
	Males		Females	
	μ	σ	μ	σ
0	7,8	2,1	7,4	1,8
1	11,7	1,6	10,8	1,5
2	13,7	1,7	13,4	2,4
3	15,6	2,2	15,5	2,5
4	18,1	2,9	17,5	2,7
5	20,6	4,2	19,7	3,4
6	22,8	4	22,3	4,1
7	25,7	4,5	25	4,4
8	28,9	5,5	28,7	5,9
9	32	6	32,2	7
10	35,2	7,6	34,3	7,1
11	40,1	8,8	39,9	9
12	44,8	10,3	45,1	10
13	48,9	10,8	50,3	10
14	56,6	12,5	51,8	8,6
15	61,5	11,7	54	9,3

16	64,8	9,6	55,7	11
17	66,8	10	57	9,3
18	68,7	10,5	56,3	9,4
19	69,7	14	58,7	10,9
[20;24]	71,2	11,1	58,7	10,7
[25;29]	75	12,2	60,9	11,6
[30;34]	77	12,8	61,8	11,8
[35;39]	77,3	12,5	62,3	11,7
[40;44]	78,2	12	63,1	12,5
[45;49]	79,4	12,6	63,8	13
[50;54]	79,8	12,8	64,8	12,5
[55;59]	79,9	12,6	66,1	13
[60;64]	79	12	66,1	12,4
[65;69]	78,7	11,7	66,8	12,5
[70;74]	78,4	11,7	65,9	12,4
[75;79]	76,3	11,6	65,2	12,4
[80;84]	75,1	11,8	62,3	11,6
[85 et +]	69,9	11,1	57,6	10,9

Height of French individuals as a function of age

The mean height of French individuals as a function of age for both males and females is given in Table B.2. The data are taken from : <http://www.auxologie.com/croissance/>

Table B.2: Mean height of French individuals as a function of age

Age	Mean height (cm)	
	Females	Males
1	72	73
2	85	85
3	93	95
4	100	102
5	106	107
6	112	114
7	117	119
8	124	125
9	129	130
10	134	135
11	140	141
12	146	146
13	154	152
14	158	159
15	161	167
16	162	171
17	163	174
18 and +	163	175

Appendix C: An experimental approach to assess the disparities in the usage trends of domestic electric lighting

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Proceedings of the ASME 2012 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference, IDETC/CIE 2012, August 12-15, 2012, Chicago, IL, USA

ABSTRACT

In a country like France, electricity consumption devoted to domestic lighting represents nearly a fifth of the total energy consumption of a building. The use of electric lighting is influenced by several factors such as the building's structural characteristics, the activities of its occupants, the lighting equipments, and the level of natural light. Designers do take into account, in their energy models, the influence of occupants on the building's overall energy consumption. However, these models still have some drawbacks regarding the comprehension of real "occupants' energy behaviors" which play an important role in the discrepancies between predicted and real energy consumptions. The behavioral factors behind occupants' usage trends of energy are still not thoroughly explored. Therefore, it is assumed that a better comprehension of these behaviors and consumption mechanisms could lead to the identification of technical solutions and energy saving potentials, thus resulting in a more robust building design.

The present paper aims to provide an insight into domestic lighting usages. The main objective is to explore the key factors (socio-demographic, economic, technical and behavioral) responsible for the disparities in lighting consumption between one household and another. For this purpose, an experiment is performed concurrently to the proposal of a lighting usage model. A micro level investigation protocol is elaborated and used to conduct in-depth studies on the usage patterns of electric lighting. The survey is conducted on a sample of 8 French households. The methodology for constructing the experimental protocol, its deployment, as well as the results obtained and their analysis are presented in this paper. The need for further qualitative and quantitative studies to better understand the usage trends of electric lighting is discussed.

Key words: Energy, household, domestic lighting, occupants, behavior, usage pattern

1 INTRODUCTION

In France, the building sector is responsible for 43% of the total final energy consumption and for 25% of the national CO₂ emissions [1]. Just recently, it has come to light that this sector may be the only one, among other economical sectors, capable of making a significant progress to be able to meet the national commitments with regard to reducing greenhouse gases. Energy consumption reduction in the building sector is thus an important step towards sustainable environment. Therefore, a better comprehension and integration of building performance determinants in the design of buildings, especially in the very early phases, has become essential.

In general, the energetic performance of a domestic building is governed by various parameters, such as its physical characteristics, its internal services systems and equipments, its external environment and most importantly its occupants [2–4]. Unreliable assumptions concerning one of these parameters could lead to significant discrepancies (up to 100%) between predicted and real energy consumptions [5].

User behavior plays an important role in determining energy consumption levels of the building, especially during the operation phase. As a matter of fact, the influence of the users is due to their presence in the building and the activities they perform including the actions they undertake in order to control their indoor environmental conditions (internal air quality, thermal comfort, visual comfort, etc.) [6]. Nevertheless, occupants' behaviors and their energy-consuming activities are still modeled as static and conventional parameters in current energy estimation models [6]. As an example, we can note that recent energy regulations such as the RT2012 [7], which is the newest building regulation in France that defines performance standards, are still showing some gaps when it comes to the integration of real occupants' energy behaviors. For instance, the lighting usage scenarios defined in RT2012 consider that occupants use artificial lighting only in the case where natural light is unavailable. Moreover, the calculation method of the mentioned norm assumes that the power of artificial lighting installed in a building is equal to 1.4 Watts per square meter, and that only 10% of lighting points will be turned on simultaneously [7].

The use of electric lighting is one of the most important sources of energy consumption. In France for example, it is responsible for nearly a fifth of the total energy demand of a residential building [8]. Despite all the efforts made to drive it down, this demand continues to increase [9]. As a matter of fact, the use of electric lighting in a dwelling is governed by various parameters related to its structural characteristics, its lighting equipments and its occupants' usage patterns. Occupants use artificial lighting in order to satisfy their own visual comfort while performing daily life activities such as cooking, eating, reading, and house cleaning. Diversities are present in the type of lighting equipments owned by households and

in their needs to use artificial light. Thus, it is hard to predict, with a good accuracy, energy consumption resulting from the use of electric lighting for a dwelling, a building or a residential area perimeter [10]. Hence, it is obvious that unrevealing the cover of the ambiguous lighting usage trends, should result in better building designs. By this, we mean that designers could have the ability to improve their technical solutions, making them more independent of usage variability by, for instance, installation of movement sensors, or automatic disconnection of lighting equipments in case of non-use. In addition, energy consumption estimations would be more accurate, service performances would be more guaranteed and appropriate and targeted incentives could be proposed. As a result, the building could be more robust vis-à-vis the variability of occupants' behaviors.

In this paper, we investigate the usage practices of artificial lighting in residential dwellings. The experimental procedure is developed coherently with the proposal of a lighting usage and activity model. The paper objective is to identify relationships between lighting usage trends and possession of equipments on one hand, and personal and constructional factors related to households on the other. After a critical review of literature, we present the investigation protocol which has been elaborated for the purpose of this study. The results of the experiment reveal the highly stochastic nature of lighting practices along with the important discrepancies in lighting consumptions between different households.

2 BACKGROUND AND RELATED WORK

Even though several studies have been carried out to understand users' behaviors and their impacts on the overall energy performance of a residential building, yet only few of them has assessed the use of domestic electric lighting. Hunt [18] was one of the first researchers who put special emphasis on the interactions between occupants and their lighting equipments. Afterwards, Newsham et al [19] and Reinhart [20] have introduced simple stochastic models to predict the use of electric lighting in office buildings. These authors have improved the standard occupancy profiles by reproducing more realistic times of arrival and departure of building users through field observations. Yet, occupants' activities, goals, comfort, mood, etc, are not modeled. Authors such as Wang et al [21] and Yamaguchi et al [22] have focused mainly on modeling occupant's presence without paying enough attention to his/her interactions with the building and the usage of equipments. The abovementioned studies have modeled essentially some invariable activities such as the use of PC's in offices, and did not deal with variable activities such as the use of lighting or other more complex activities encountered especially in residential buildings.

In literature, we can also find studies on the variations in the pattern and quantum of household energy requirements. Working on a sample of Indian households, Pachauri et al. [4]

have revealed some important facts related to the direct and indirect factors causing such variations. In order to carry their study, Pachauri et al. have used data on household consumption expenditure from the India's national survey samples. These explanatory data included economic variables (total house expenditure), demographic variables (location of dwelling, number of household members), and dwelling attributes (covered area of dwelling, construction type, and dwelling type). In their analysis, the authors explored some important relationships between the aforementioned variables. For instance, the results have shown that the total household income level is the most important explanatory variable causing variation in energy requirements across Indian households.

More detailed studies have tackled the usage of electric lighting in residential buildings. For example, Stokes et al. [11] developed a model to predict long-term lighting demands in the UK. Their model, which is a part of a more generalized load model, is based on monitoring data collected from a sample of 100 UK houses. Using these measured data (coming from national studies); they have developed a stochastic method to account for various parameters, including the number of occupants, appliance ownership, income and lifestyle. Stokes et al. highlighted that their model was not intended to capture all elements of diversity especially the detailed behavior of occupants. For instance, they did not take into account the difference in occupancy patterns between different households.

Stokes et al. [12] conducted another study to examine lighting use from a socio-technical perspective by drawing on recent in-depth interviews. Their study revealed some important findings, regarding the use patterns of lightings and the purchase decisions surrounding both bulbs and light fixtures. It has shown that lighting is intrinsically linked to the mood and well-being of occupants. For example, they found that the technology of low energy lighting fails to provide people with the kind of control and illumination that is required, and that the desire to have stylish interiors by using artificial light can over-ride environmental principles.

Other authors have established some models to simulate the use of domestic electric lighting. For example, Widén et al. [13] have developed a stochastic bottom-up model of domestic lighting demand. Their model features mainly the domestic occupancy patterns and the daylight availability, and to transforms these patterns into lighting demand.

Another model was established by Richardson et al. [14] in the scope of developing a comprehensive domestic electricity demand model for residential buildings in UK. This model tackles some important features of real lighting usages such as occupant presence, types of lighting equipments installed, and the presence of natural light. The main drawback of this model is that it is based only on two physical input factors which are the outdoor irradiance and the active occupancy in the dwelling, without considering the factors related to the random behaviors of its occupants. Bladh et al. [15] have also addressed the exploration of hidden factors related to the usage patterns of domestic lighting in Swedish households. Their study is

based on detailed metering and interview data from seven households, combined with other metered data from a larger sample of Swedish households. The in-depth interviews were conducted at the household level to find out the needs and considerations behind the selection, location and use of lamps.

As we have seen in the literature review, most of the studies that addressed the use of domestic lighting have adopted approaches based on field monitored data and statistical surveys. These studies have mainly concentrated on developing stochastic models to estimate lighting energy demand [11,13,14], on identifying possible energy savings [23,24], on monitoring energy consumptions [10], or even on developing methodologies to evaluate energy efficiency lighting programs and promotion campaigns [16,17]. We do not find many in-depth studies about households' usage-patterns of electric lighting. The majority of the studies do not address clearly the relations between the acquisition of lighting appliances and the occupants' usage patterns on the one hand, and the socio-economic, demographic, technical and behavioral factors on the other hand. Nevertheless, some authors such as Bladh et al [15] and Stokes et al [12] have conducted exhaustive investigations and get out with some conclusions regarding the vague notions of electric lighting consumptions. However, there are still some important aspects that have not been tackled. For instance, no clear identification of domestic activities necessitating lighting usage has been established. Moreover, these studies do not mention the discrepancies related to the household's possession of lighting equipments (equipments already installed in the dwelling, or equipments owned by the occupants?). Besides, no clear correlations have been made between the types of household and its corresponding energy consumption due to light usage.

3 METHODOLOGY

Given the abovementioned conclusions, one can deduce that the examination of the key drivers of domestic lighting usage and its corresponding energy consumption is not a trivial issue. Thus, a thorough comprehension of these influencing drivers is needed. The only way to do this is by conducting deep qualitative experimental studies and interviews vis-à-vis the lighting users themselves.

In the scope of these considerations, we elaborated an exhaustive investigation protocol to assess the realities underlying the arbitrary character of domestic lighting usage. The protocol was then deployed on 8 French households so that to validate its reliability and to start feeding our database. In this study, we intend to use the results of these 8 extensive field observations in order to scrutinize the main factors influencing the lighting usage trends, such as the socio-demographic and economic characteristics of households, the purchase of lighting equipments,

the patterns of their usages and the needs behind those usages. The investigation protocol used for this study is presented in the following section.

3.1 A Micro-Level Investigation Protocol

The aim of this protocol is to answer the following questions: Why do people use lighting? For which purpose and what activities? What are the lighting equipments that can be found in French dwellings? How do individuals choose their lighting appliances and how do they distribute these equipments in their houses? Why and how do use-patterns of lighting differ from one household to another?

Keeping these questions in mind, the protocol was divided into two main steps. The first step consists of a survey designed to capture the main characteristics related to occupants, their dwellings, and their lighting equipments, whilst the second step consists of log-sheets filled by the occupants over given days. These log-sheets were designed to capture the usage patterns of electric lighting (Who, when, what, why and how).

3.1.1 First Step of the Investigation Protocol: Capturing household-related characteristics

This survey is divided into two parts. The first part concerns the personal characteristics of households. It draws information about the number of individuals consisting the household (adults and children), their ages, gender, professional activities (employee, retired, housewife, student, etc.), as well as their hours of presence in the dwelling.

The second part concerns the physical characteristics of the dwelling as well as the lighting equipments. In this part, we ask each household to make a simple drawing of his/her dwelling indicating the following information: nature of each room (kitchen, bedroom, etc) and its surface area, the orientations, and the locations of doors and windows. Next, the participant is asked to indicate the location of his/her lighting equipments all over the surface of the dwelling by drawing a small circle to represent each lighting appliance and assigning a number to each of them. Afterwards, a table is to be filled containing the characteristics for all lighting equipments: technology, style, number of bulbs, power rating, and the setting mode (ON/OFF switch, dimmer, etc.). The participant is also asked to indicate whether the lighting equipment was already installed in the dwelling before he moves in or it was purchased afterwards. Table C.1 summarizes the information collected from this survey.

Table C.1: Data Surveyed Concerning Occupant-Related and Dwelling –Related Characteristics

Category of information	Information surveyed
Occupant's personal characteristics	Number of occupants per household Age Gender Professional activity Economic situation Occupation periods throughout the day (for weekdays and weekends) Special physiological problems related to the use of light
Dwelling constructional characteristics	Region Floor Type of dwelling (studio, 2-roomed, etc.) Direction Nature of different rooms Surfaces of different rooms Positions of windows and doors
Lighting equipments in possession	Location Type Style Number of bulbs for each equipment Power ratings Setting mode Possession (already existing or occupant's property) Reasons for introducing/purchasing of equipments

For the sake of having a wise classification of studied households according to their socio-economic and demographic characteristics, we adopt the classification elaborated by CREDOC (Research Center for the Study and Observation of Living in France) [26] who developed and validated a new indicator to classify the French population in 15 different categories based on the notion of "life situations" (Table C.2). As for the economic situation, the study of CREDOC differentiates between 5 economic categories (Table C.3). The income variable is taken at the household level and not at the individual level.

Table C.2: Categorization of French Population (From [26])

Different categories of French population with their respective percentages	
<i>Young without children</i>	<ol style="list-style-type: none"> 1. Single inactive and living in their parents' home (6%) 2. Independent with low income (6%) 3. Independent with average to high income (4%)
<i>Families</i>	<ol style="list-style-type: none"> 4. Young (18 to 34 years old) with 1 or 2 children and average to high income (3%) 5. 25 to 64 years old (mostly between 35 and 44) with 1 or 2 children and average to high income (10%) 6. 35 to 64 (mostly older than 45) large family with (3 or more children) and average to high income (6%) 7. 25 to 54 years old with 1 child and low income (9%) 8. 25 to 44 years old with 2 to 3 children and low income (10%) 9. 45 to 64 years old with 2 to 3 children and low income (45%)
Adults without children (aged between 35 and 64 years old)	<ol style="list-style-type: none"> 10. Single aged 35 to 64 years old (5%) 11. 35 to 54 years old couple with low income (2%) 12. Couple (mostly between 45 and 54 years old) with average to high income (4%)
Retired	<ol style="list-style-type: none"> 13. Single or couple (> 55 years old) with low income (13%) 14. Single or couple (> 55 years old) with average to high income (10%) 15. Household (> 55 years old) with more than 2 persons (4%)

In our study on lighting usage, we have asked each household to choose, using Table C.2, the category of population to which he/she belongs. Later on in this paper, we examine if there are relations between each of these groups and the lighting consumption patterns

3.1.2 Second Step of the Investigation Protocol: Capturing Lighting Usage

Patterns

After acquiring the most important features regarding the occupants, their dwelling and their lighting equipments in the first part of the protocol, the second step consists of investigating the usage patterns of light. For this purpose, we have elaborated log-sheets to be addressed to occupants so that to get the panorama of their usage of light over given days (lighting scenarios). For each household, representative logs were obtained over one weekday and one weekend day. The idea behind these log-sheets is to provide a real image of lighting usage scenarios (Who, when, what, why and how). Table C.4 summarizes the data collected from the log-sheets.

Table C.3: Economic categories of French population (from [26])

Category	Monthly income
<i>Low income</i>	<ul style="list-style-type: none"> • Less than 1220 € • Between 1220 € and 1830 €
<i>Average to High income</i>	<ul style="list-style-type: none"> • Between 1830 € and 3658 € • Between 3658 € and 5488 € • More than 5488 €

Table C.4: Data collected from log-sheets

Log-sheet	Information required
<i>Situation of use of electric light</i>	<ul style="list-style-type: none"> • Which equipment was used • Who used it • The reason for using the light • Time of usage • The level of natural light at the time of usage • The present luminosity before putting the light ON • The state of curtains (opened or closed)

2 Deployment of the Protocol

The experimental protocol was deployed on a sample of 8 French households chosen according to the number of people and age criteria. For each of the selected households, a brief interview was conducted with one or more of the adults responsible of the family. The interview aimed to explain the study and to enlighten the participant on the modalities to be followed in order to reply for the questions evoked in the experimental protocol. For some participants, the interview was carried out in their households where we have examined by our own eyes the elements that were supposed to be filled in survey, whilst for others the interviews were done outside their households. The survey has been conducted between December 2011 and January 2012. During this period, the presence of natural light is low and the need of artificial lighting is more pronounced.

Presentation of Households considered in the study

The 8 households involved in the study live in the region of Paris and its suburbs. Here are their characteristics:

Household 1: Single young male aged 26. He lives in a rented 2-room apartment with an area of 40 m². The apartment is situated on the second floor and has a balcony from the north-east side with an area of 4 m². The occupant works full time and he does not work on weekends. This household belongs to category 3 (Table C.2).

Household 2: Single young female aged 28. She lives in a rented studio of 20 m² area. She works full time and doesn't work on week-ends. This household belongs to category 3.

Household 3: Young and childless couple. The male is aged 31 and the female is aged 28. They live in their own 3-room apartment of 50 m². The male works full time except weekends, while the female is unemployed and spends most of her time at home. This household belongs to category 3.

Household 4: Young couple with no child. The male is aged 26 and the female 24. They live in an owned 3-room apartment of 56 m². The apartment is located on the third floor and has a balcony of 5 m² from the west side. The male works fulltime except weekends, while the female is a university student. This household belongs to category 3.

Household 5: Young family with a 3-years-old child. The man is aged 28 and the woman 32. They live in an apartment of 50 m² situated on the ground floor of a three-floor building. Both of them work full time. The woman works one weekend out of two. This household belongs to category 4.

Household 6: Young family with 2 children (1 and 4 years old). They live in a rented apartment of 60 m² situated on the first floor. Both of parents work full time. The wife does not work on Wednesdays because she supervises her two children. This household belongs to category 4.

Household 7: Middle-aged family with 2 children (12 and 20 years old). The husband is aged 48 and his wife 43. They live in a rented 4-room apartment of 86 m² situated on the fifth floor. Both of parents work fulltime. The 2 children are students. The mother does not work on Wednesdays since she supervises her younger child at home. This household belongs to category 5.

Household 8: An old married couple. They are aged 60 and 62. They live in an owned detached house of 55 m². Both of them work full time. This household belongs to category 12.

4. RESULTS AND DISCUSSIONS

4.1 Installations of Lighting Equipments

The results obtained from the in-depth investigations have shown significant differences in the lighting installations between one household and another. These differences are present for both bulb types and lighting fixtures. Table C.5 shows the distribution of the possession of lighting equipments for each household. The bulbs are classified into five categories: standard incandescent, Halogen, CFL (Compact fluorescent lamp), florescent strip and LED (light emitting diode).

By considering the entire sample, an average of 18 bulbs per household is found. However, large disparities are detected between households according to the type of the dwelling and its surface area. For instance, the number of bulbs in dwelling 2 (studio 20 m²) is 4, while it reaches 24 bulbs in dwelling 4 (3-room apartment).

The results in Figure C.1 show that, for the entire sample, the majority of bulbs are of halogen and incandescent types with 39% and 37% respectively. The CFL's, although known to be energy efficient, are rarely present (only 12%). Even lower percentages are revealed for florescent strips and LED's.

Table C.5: Distribution of bulb-types per household

House-hold	Incandescent	Halogen	CFL	Florescent strip	LED
1	5	2	7	0	0
2	3	1	0	0	0
3	10	15	0	0	0
4	13	9	0	2	0
5	1	13	2	0	4
6	6	6	6	1	0
7	6	5	0	2	3
8	7	4	2	2	3

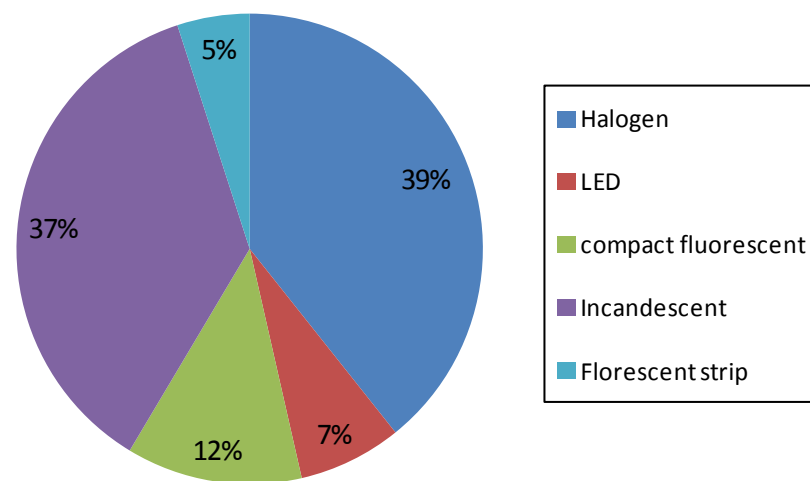


Figure C.1: Distribution of bulb types: averages for the entire sample

A closer analysis of the survey data (Table C.5) reveals that individual bulb type distributions are quite dispersed. For instance, no CFL bulbs are installed in household 3. When questioned about the reason, the individuals of this household explain this by expressing their worry about the harmful effect of CFL's on health, basing their idea on media information.

As for the other households, the occupants have complained of the performance of CFL's, notably the time needed by such bulbs to reach maximum luminance. As for LED bulbs, the

investigations have shown that they are avoided due to their high price and relatively weak luminance. In contrast, halogen and incandescent lamps which consume a lot more than CFL's are widely present in the sample dwellings. The occupants manifested their interest in having such types of bulbs due to their good lighting quality and low price.

Construction-related factors are identified as another reason behind the choice of specific types of bulbs. People tend to purchase bulbs that are simply compatible with the pre-existing fixtures in the dwelling. This important point was evoked by several households of our sample. In household-5 for instance, the acquisition of a large number of halogen bulbs comes from the fact that their landlord had installed spot fixtures in the kitchen and the sitting room. The occupants of this dwelling declared that they are obliged to choose between LED and halogen bulbs, the only types compatible with spot fixtures. Due to their better luminance and competitive price, the decision settled on the halogen type. Figure C.2 shows a comparison between the number of lighting fixtures introduced by the occupants and those already present in the dwelling. For household 2, almost 70% out of the total 10 fixtures were present in the dwelling before the occupant moved in.

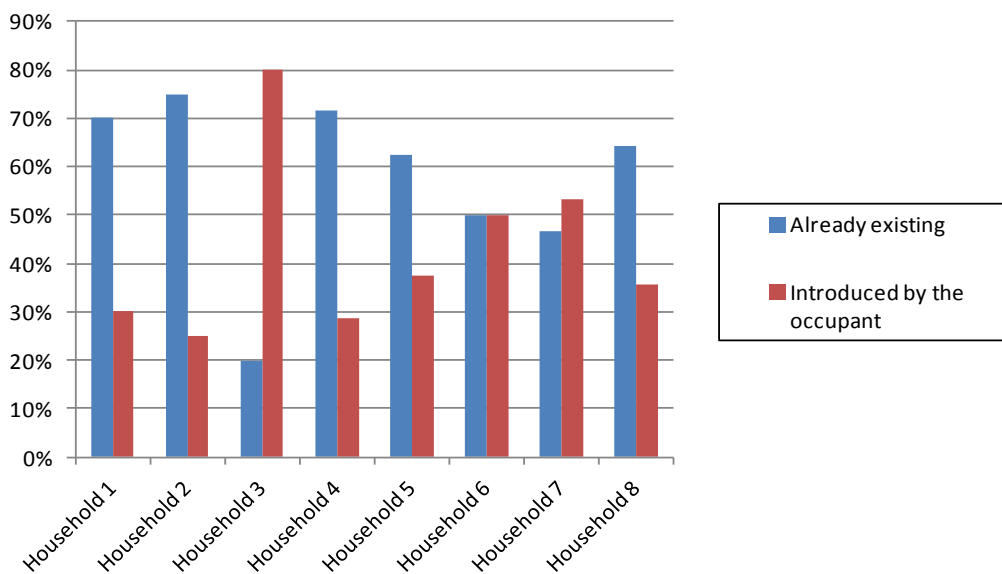


Figure C.2: Number of lighting fixtures for each household

There are several reasons why people introduce new lighting fixtures to their houses. Some of these reasons are totally independent of the occupant real needs (such as decoration purposes, received gifts, etc.). On the other hand, most of the introduced fixtures aim to compensate for insufficient (weak) or uncomfortable lighting (too strong) from the pre-installed equipment. Insufficient lighting can be also due to the orientation of the apartment.

4.2 Location of lighting equipments

The location of lighting equipments in the different rooms of a dwelling plays a very important role in identifying the use of light and the energy consumption resulting from this usage. Investigations of this aspect have revealed that occupants do not have full control of the location of their lighting appliances. As presented in Figure C.2, a majority of the lighting fixtures are pre-installed by the landlords and their locations are hardly modified (ceiling-mounted lights for instance). Households are able to choose the location only for the equipments they own. In general, people tend to place the light fixtures where they feel that the existing lighting is insufficient. The comfort threshold for light is estimated differently by each household. For example, when moving to his/her apartment, the occupant in household 1 discovered the presence of a low-consuming bulb at the entrance and a high consuming bulb in the bathroom. Given that the use of light is more frequent and for longer durations in the bathroom, the occupant decided to interchange these two bulbs in order to decrease the consumption, and to avoid the slow illumination of the low-consuming bulb at the entrance. Another factor influencing the location of lighting appliances is the need behind using that light i.e. the activities requiring the luminosity. In our survey, we notice that most households have introduced equipments with high luminance in the sitting room. This point is explored thoroughly in the following section.

4.3 Exploring the needs behind artificial light usage

The studies presented earlier in the literature review have identified some of the important aspects behind lighting usage.

In Sweden, Norway and UK, coziness was found to be an important feature in domestic lighting usage [16, 20]. From our study, we can confirm that this conclusion is also valid for the French households. It has been found that lighting is used not only to gain better vision when natural light is dim, but also to adjust the ambience and the well-being of occupants.

One of the most important aspects that we seek from this study is to uncover the different needs of light. Why do people use artificial light? And for what domestic activities do they use it?

As a matter of fact, the study concludes that occupants use light with almost all the activities they perform during their presence in the dwelling. They use light while preparing food, watching TV, going to restrooms, accompanying children to bed, etc. Figure C.3 shows an example distribution of lighting usage durations with different daily activities of household 3. The total lighting usage duration is around 744 minutes per day. For this household, the results show that “watching TV in the evening” is the most time-consuming activity during the day, with about 43% of total usage time. The activity “cleaning household” comes in the second place with around 16% of the total. The reason is that one of the individuals of this household

is unemployed and spends a lot of time performing domestic activities, including house cleaning. Other activities are present with shorter durations such as preparing food (9%), eating (6%) and reading/working (4%).

Figure C.4 presents the distribution of lighting usage durations per activity for all of the households. The results suggest that the most light-consuming activities, in term of usage duration, are practically the same for the different dwellings. “Watching TV in the evening” reveals light-consumption durations between two to five hours (household 1 and 4). Coming next are activities such as “preparing food”, “eating”, “reading /working”, “going to restrooms”, etc.

In household 5, the activity “Accompanying children to bed/sleeping” shows long lighting-usage duration reaching 8 hours per day. When asked about this, the parents declared that they keep the light lit during all the night in the room of their 3-year old child. In household 7, the activity “preparing/taking breakfast” shows long usage durations. The reason behind this is that the four family members take their breakfast separately. In contrast, household 8 shows shorter light-usage duration for the same activity since both individuals living there take breakfast together. The activity “reading/working” presents high time usage in household 2 where a single young female lives alone in a studio. The occupant has confirmed this fact during the interview by declaring that she studies for 1 to 3 hours daily.

For nearly all of the households, the duration of having lunch or dinner (eating) is almost the same regardless of the household characteristics (single, family, etc.).

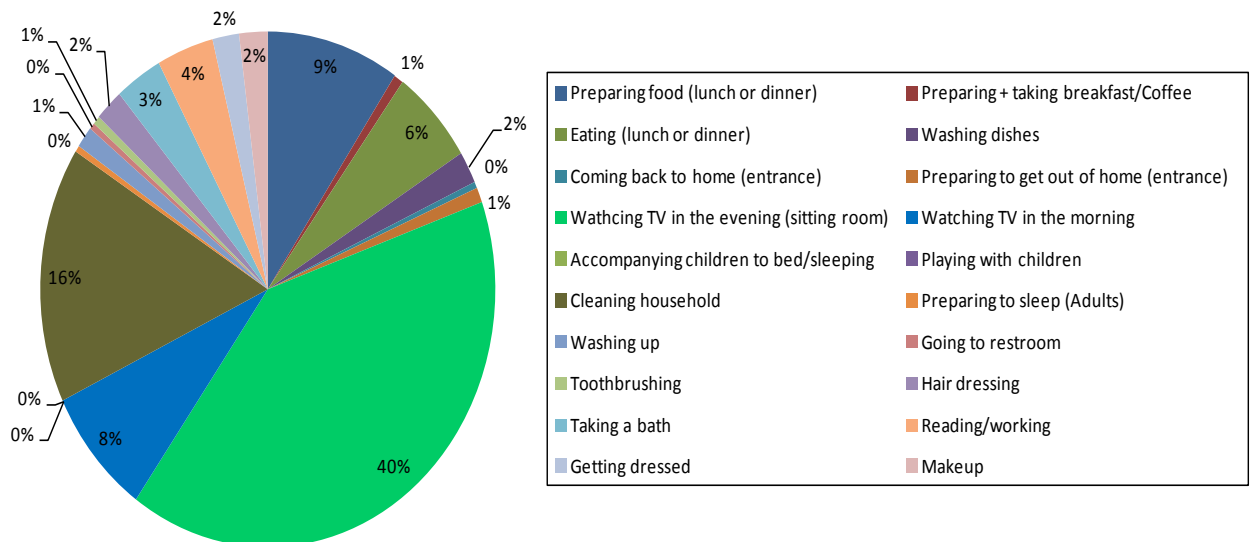


Figure C.3: Distribution of lighting usage durations through a weekday (household 3)

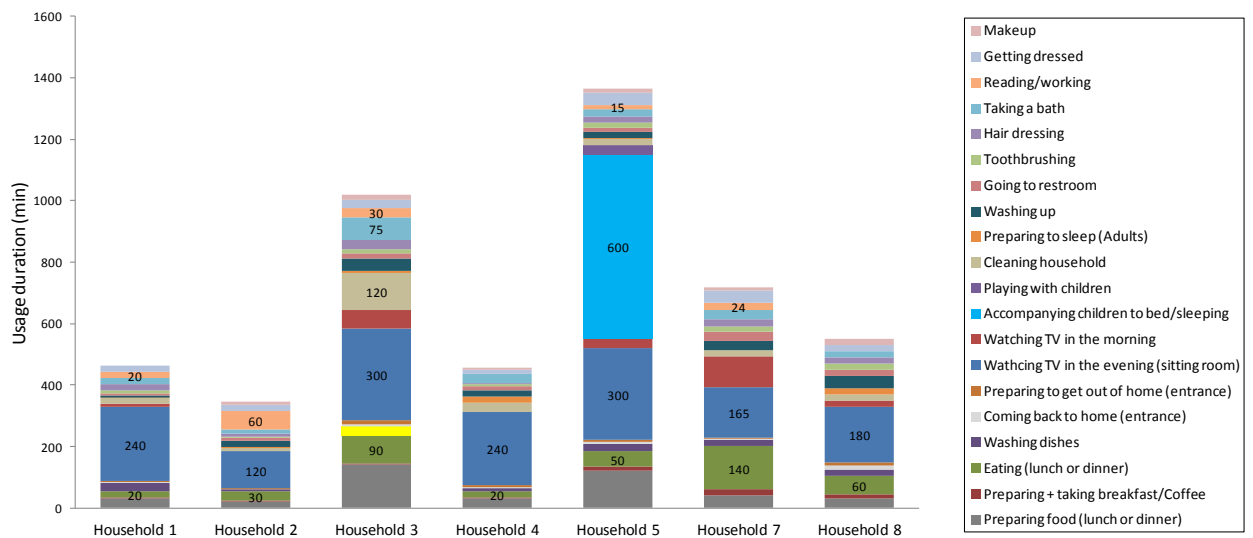


Figure C.4: Distribution of lighting usage durations for all households (week-days)

It is relevant to mention here that the survey resulting for weekend days shows the same light-using activities as for weekdays, but with differences regarding the duration and frequencies of these activities. For example, families spend more time preparing food and eating, children and teenagers spend more time playing video games, etc.

As a result, we can deduce that the needs behind using artificial light are influenced directly by occupants' attributes, the type of lighting equipments they have, and the type of dwelling they occupy. Hence, electricity consumption due to light-use could differ completely from one household to another. Therefore, a good correlation between household types and their corresponding lighting needs is of great interest.

4.4 Energy consumption related to lighting use

For each of the dwellings present in the sample, the power consumption due to lighting use is calculated, except for dwelling 6 because of data shortage. Figure C.5 presents the distribution of these consumptions per activity. The power consumed to perform an activity is calculated by multiplying the duration of the latter by the power rating of the bulb(s) used to perform it.

The results show that energy consumption due to light-use is influenced by several factors. The first one is the presence of occupants at home. The more people are present at home, the more they use light to perform domestic activities. For example, singles and couples with no children are less present at their homes compared to families with children, who are more present on Wednesday afternoon (school holiday) and on weekends. The second factor is related to the type of equipments. The more households possess high-consuming bulbs (incandescent and halogen), the higher is their lighting consumption. In household 3 for instance, where the bulbs are of halogen and incandescent types only, the consumption is about 2.9 KWH per day, that is five times higher than that of household 5 which is of the same

apartment type but with less high-consuming bulbs and more energy-efficient bulbs (see Table C.5). The third factor influencing lighting consumption is related to the domestic activities executed within the dwellings. The frequency and the duration of these activities have a direct impact on the energy consumption related to light use. For instance, Figure C.5 shows that the most energy-consuming activity, in terms of light use, is “watching TV in the evening” which is the dominant activity for all households. The fact that the occupants watch TV in the evening underlies other secondary activities (such as having a tea, playing with children, surfing internet, etc.) being performed in parallel with the primary activity which is having the TV turned on.

Obviously, all of the three abovementioned factors (presence, equipments and activities) are directly related to the occupants’ attributes and their life style.

Hence, one can conclude that having a good representation of the occupancy profiles, the domestic activities, and the lighting equipments of a household, could result in a good representative insight to the lighting consumption of the latter.

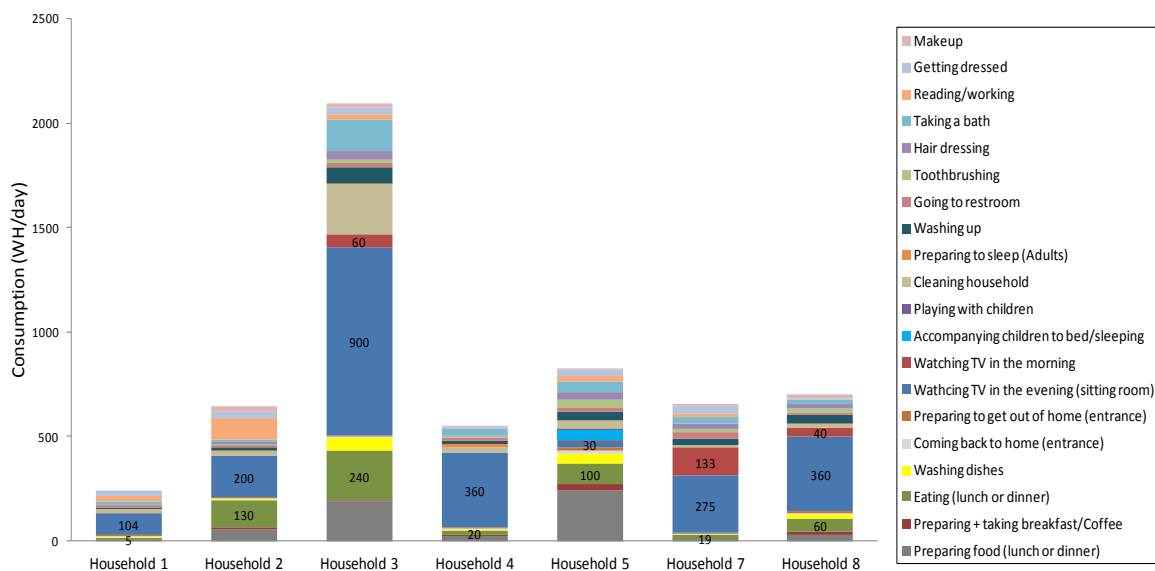


Figure C.5: Distribution of energy consumption for domestic lighting per activity (weekdays)

5. CONCLUSIONS AND PERSPECTIVES

In this study, we explore the different factors responsible for the disparities in lighting consumption between one household and another. A micro level investigation protocol has been elaborated and used to conduct in-depth studies on the usage patterns of domestic electric lighting. The main results of the survey suggest that the use of electric lighting is highly influenced by the socio-demographic and economic characteristics of households, their selection of lighting equipments, and their quantities of activities.

The survey enabled us to have an idea concerning the major types of artificial lighting equipments that could be found in French dwellings, where we have identified five main types. These equipments are present in the dwelling either because they were installed by the landlord, or introduced by the tenant as for to compensate for the non-efficiency of the pre-existing lamps, or simply to be used as decoration.

It is found that lighting is used not only to gain better vision when natural light is dim, but also to adjust the ambience and the well-being of occupants. In this survey, we have distinguished the most important reasons for which occupants use the light at their homes. A list of twenty different activities necessitating light usage is established. Of course, more similar qualitative studies are needed in order to have the full list of these activities.

The results highlight as well the impact of design decisions on the consumption behaviors of households. For instance, the orientation of the dwelling and the lighting technologies installed by constructors can play a significant role in determining lighting consumptions.

This paper validates the reliability of using in-depth studies for assessing energy demand in domestic buildings. Such exhaustive protocols can be very useful for understanding the ambiguous nature of occupant behaviors vis-à-vis building's energy consumption. Consequently, better design solutions could be proposed. The installation of energy-efficient lamps in rooms where the usage of light is more frequent (sitting room for example), and the integration of dimmer switches are good examples of design decisions that can be made.

It is obvious that there exist some important correlations between lighting usage and consumption on the one hand, and the occupants' attributes (economic, social, cultural, lifestyle etc.) as well as the dwelling attributes on the other hand. For the purpose of establishing these correlations, further qualitative and quantitative studies must be conducted over larger samples and during for longer periods in order to better understand the different lighting usage trends. This will lead to the development of more detailed lighting usage models, and eventually improve the predictability of global energy estimations in residential buildings.

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