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An activity-based modelling framework for quantifying occupants' energy consumption in residential buildings

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ABSTRACT

The residential building is a major energy consumer and pollution source worldwide. The shift towards constructing energy-efficient buildings is impelling higher performance. In sustainable building, occupants become a major source of uncertainty in energy consumption. Yet, energy simulation tools often account for occupant behaviour through predefined fixed consumption profiles. Therefore, energy and buildings experts are in need for more precise methods for better forecasting the influence of occupants on the building performance. An activity-based framework for quantifying occupant-related energy consumption is proposed. The energy consumption is quantified per domestic activity as a function of households' socio-demographic and economic attributes. The aggregation of such domestic activity energy consumption provides an accurate estimation of the household energy consumption per daily, monthly and annually periods. First, a literature review about residential energy consumption and the existing modelling approaches is presented. Second, a systematic breakdown structure of energy end-uses is proposed. The activity-based framework is then introduced. An application example is demonstrated together with simulation results. Finally, model's utility is outlined and its possible implications are discussed.

1. Introduction

The building sector is a substantial energy consumer and environment pollutant in most countries. It accounts for important shares, ranging between 16 and 50%, of national energy consumptions worldwide [1–4]. In order to reduce these consumptions and emissions and to promote sustainable development, authorities around the globe are thus establishing energy directives and regulations that help optimising building's performance. Examples of these directives are the European "Energy Performance of Buildings" (or EPBD) and the latest French thermal regulation RT2012 [5]. Moreover, various energy efficiency labels and green building rating systems already exist worldwide, such as BREEAM in the U.K, LEED in the United States, and BBC-Effinergie in France [6]. Such energy labels and certifications encourage the use of best practices and the development of energy efficiency solutions that go beyond the minimum requirements stipulated by standards and regulations. As a result of such norms and labels, building actors are tending progressively to construct energy-efficient and green buildings. This is also accompanied with new market expectations such as the "energy performance contracts" that impel constructors to deliver energy-efficient buildings and to guarantee their performance level for a number of years [7]. As a result, a better comprehension and integration of building performance determinants into the design of buildings has become essential. At the same time and due to the deployment of smart meter, providing a solution for visualizing real time energy consumption is now a legal requirement. A better comprehension of such occupants' behaviours is a promising way to engage occupants towards a reduction of their energy consumptions by the mean of nudges dissemination.

The energy performance of a building is governed by various parameters, such as its physical characteristics, its external environment, its internal services systems and equipments, and most importantly the behaviour of its occupants [8–10]. Industrial energy simulation tools, such as Energy Plus, eQUEST, ESP-r and TRNSYS, focus primarily on the structural behaviour of buildings and their relations to specific environmental conditions while taking insufficiently the role of the occupants into account [11,12]. This simplification of occupants' behaviour may leads to unrealistic energy estimates [11,13]. Therefore, energy and buildings experts are in need for tools that enable them to

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model more accurately the influence of occupants on the whole-building performance. Such models can thereby be used as complementary tools for existing industrial ones in order to provide more accurate estimates of residential energy consumption and accompany inhabitants towards the reduction of the energy consumption. Consequently, some design and technical solutions may be better adapted and energy performance contracts (guarantees) may be better adjusted.

2. Literature review

2.1. Occupants and residential energy consumption

The residential sector consumes secondary energy, i.e. electricity and hydrogen produced from primary energy sources such as coal, natural gas, petroleum, nuclear energy and renewable energy sources, which is used by occupants for performing their domestic activities. Several studies pointed out the major end-use groups of secondary energy such as space heating, space cooling, domestic hot water, as well as appliances and lighting [14–17]. Building's energy consumption is highly dependent on the performance of its systems and the general behaviour of the occupants [18]. According to Robinson [19], the most complex processes taking place within buildings are those that result from human behaviour. Authors such as Emery and Kippenhan [20], Masoso and Grobler [2], and Guerra-Santin and Itard [21] also reveal occupants' influence on residential energy consumption. Authors such as Page et al. [22], Robinson [19] and Wilke et al. [18] show that the influence of occupants can be modelled by their presence, 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 the indoor environment (e.g., lighting and HVAC).

Occupant behaviour is considered as a substantial source of uncertainty in energy modelling since energy use can vary dramatically between different households [23–26]. Swan and Ugursal [15] reveal that occupant behaviour in residential buildings varies widely and can impact energy consumption by as much as 100% for a given dwelling. This variation is mainly due to the variability in occupant profiles. Literature confirms the high correlations between household attributes on the one hand, and domestic appliances ownership levels, their energy rating, and their use patterns on the other [27–29]. For instance, Yun et al. [30] affirm that household income is an important factor in determining ownership of air conditioning equipments. Barr et al. [31] explain that the environmental concern is the major determinant for the purchase of energy-saving appliances such as washing machines, cookers, and dishwashers. Pachauri [9] concludes that the total household income level may cause high variations in energy requirements across Indian households. Lutzenhiser et al. [32] confirm that household attributes such as income, education, family size, occupation hours, and household are highly influential on energy consumption. Guerin et al. [33] identify household income, age, education level, home ownership, desire for comfort, and energy conservation incentives as influencing factors. Similar variables are also reported by Nugroho et al. [34] and Santamouris et al. [35]. McLoughlin et al. [36] identify the number of occupants, disposable income, head-of-household age, tenure type, social group, education level, and appliance ownership as the most influencing factors on residential energy consumption. To summarize, considering the energy consumption of household in green or passive building is highly dependent occupants' behaviors, appliances and devices and the way they interact each other, all the aforementioned factors are directly or indirectly (income, education, etc . . .) occupant driven.

2.2. Modelling energy consumption in residential buildings

A number of techniques and approaches have been developed to model energy consumption in residential buildings. According to Swan and Ugursal [15], these approaches are either top-down (econometric or technological) or bottom-up (statistical or engineering) approaches, where each of them comprise a number of scientific techniques [15,36]. To model occupant-related residential energy consumption, some researchers use sub-metering on measured data in order to derive representational loads of households' energy use, and thus deduce estimates of buildings' energy consumption. Authors such as Seryak and Kissock [24], Yohanis et al. [37] adopted such an approach. Although such frameworks can generate representative load profiles and provide some insights about occupants' role in energy consumption, they do not depict occupants' behaviour and preferences towards energy consumption. Another widespread modelling approach is uses of stochastic techniques for simulating occupancy patterns and various energy-load schedules. This second approach uses other source of information, namely the time use surveys (TUS), instead of using sub-metering data, The TUS are large-scale time-use surveys conducted at the national level, where each TUS record contains information on 24-hour period of activities of a given individual [38]. Then by applying stochastic techniques such as Monte Carlo Markov Chains (MCMC), daily activity patterns of energy consumption may be derived. Shimoda [39] uses data from 2000 Japanese Time-Use Survey (JTUS) to create typical occupant schedules for residential end-use energy simulations of Osaka City. Tanimoto [40] proposes 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 [41]. Richardson et al. [42] introduce a Markov-chain technique to generate synthetic active occupancy patterns, based upon time-use surveys in the United Kingdom. The stochastic model proposed by these authors provides a mapping between occupants' activities (state) on the one hand and appliance use on the other, creating thus highly resolved synthetic energy demand data. In their results, Richardson et al. [42] find good match between occupancy profiles yielded by the model and real profiles taken from the TUS data. Based on this occupancy model, the same authors developed a lighting model and a domestic electricity demand model [43,44]. Widén and Wäckelgård [45] 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 each of these activities to its corresponding domestic appliance(s). By defining load patterns for each appliance, they are capable to estimate the total electricity demand per household. The authors show that realistic demand patterns can be generated from these activity sequences. Muratori [46] and Wilke et al. [18] use heterogeneous Markov chains to model domestic activity patterns of individuals and to predict energy consumption of households. Subbiah [47] uses American TUS data for developing a disaggregated energy demand-modelling framework that estimates energy demand profiles based on individual-level and building-level energy-consuming activities. Subbiah [47] 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.

Other approaches stemming from artificial intelligence domain have started to be applied for modelling the dynamic aspects of energy consumption in buildings. Kashif et al. [13] propose a conceptual framework to simulate dynamic group behaviour by using an agent-based approach. The authors use this framework to