STOCHASTIC SIMULATION OF OCCUPANT PRESENCE AND BEHAVIOUR IN BUILDINGS

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ABSTRACT

While most current building simulation tools consider occupants as predictable robots the true nature of human behaviour is more complex. This article describes a set of stochastic models aimed at capturing this complexity by decoupling occupant presence from occupant behaviour, then considering separately each means of occupant interaction (use of appliances, of windows, of lighting, etc.) with the building and finally modeling each of these appropriately. The model of occupant presence is unique in that it generates time series that have proven themselves to be realistic at both hourly and daily time scales. That of window opening assigns personal levels of tolerance to each occupant who thereafter reacts to indoor stimuli. The appliance model attributes devices to a zone, then reproduces the typical use of these by the occupants present, thereby generating a realistic variety in values of energy consumption and peak loads.

KEYWORDS

Occupant presence, occupant behaviour, stochastic processes, Markov chains

INTRODUCTION

Various factors play a part in the energy consumption of a building : its physical properties, the equipment installed to maintain the desired internal environment (Heating Ventilation Air-Conditioning system, auxiliary production of electricity or hot water), the outdoor environment and the behaviour of its occupants. While relatively good progress has been made in the simulation of the first three factors, the latter has generally been based on fixed profiles of typical occupant presence and associated implications of their presence. As a result the randomness linked to occupants, i.e. the differences in behaviour between occupants and the variation in time of each behaviour, plays an ever more important part in the discrepancy between the simulated and real performances of buildings. This is most relevant in estimating the peak demand of energy (for heating, cooling, electrical appliances, etc.) which in turn influences the choice of technology and the size of the equipment installed to service the building. It is also important in predicting the comfort of a building's occupants.

State of the art

The effects of occupants on a building's energy consumption are varied: people give off heat and "pollutants" (water vapour, odours, CO_2) that add to the buildings internal gains and influence the occupants' comfort. Most building simulation tools integrate the effects of occupant presence within their calculations but in a very simplified way, usually considering all occupants to be present according to a fixed schedule and multiplying the number of occupants by fixed values of metabolic heat gain. Other profiles, e.g. relating to small power or lighting gains, may also be entered on a similar basis. Occupants interaction with window openings tend either to be defined by fixed schedules or by deterministic responses to physical stimuli. The most advanced of such inputs would be so-called "diversity profiles". These summarise measurements made on many buildings and propose profiles for various categories of internal gains and types of buildings (Abushakra et al. 2001).

There are however models that do not consider the occupant in an averaged way yet that are specific to a means of influence of the occupant on the building. In the field of daylighting, the Lightswitch software (Reinhart 2004) proposes a sophisticated model for the interaction of occupants with blinds and lighting systems; their presence is determined by using a simplified stochastic model of arrival and departure. In the same field Wang (Wang et al. 2005) pointed out the importance for such lighting models to be able to simulate the typical short periods of presence and absence of an occupant in an office. She proposed an elegant method based on Poisson distributions for the generation of realistic profiles of daily presence. Fritsch (Fritsch et al. 1990) was the first to propose a model based on Markov chains for the random opening of windows by occupants. This later inspired Tanimoto (Tanimoto and Hagishima 2005) to use a similar model for the use of air-conditioning systems while Nicol (2001) and Herkel (Herkel et al. 2005) adopted a static rather than dynamic approach to window opening behaviour as a function of external conditions based on logit distributions. The latest use of Markov chains to simulate occupant presence (and their use of computers) within offices of a building was developed by Yamaguchi (Yamaguchi et al. 2003). The model is integrated into a software tool

developed to explore the optimal way for covering a neighbourhood's energy needs. Although there exists a platform for the integration of occupant models (Bourgeois et al. 2006), i.e. occupants' presence and their effect on the building, there is to date no complete and interlinked set of models considering all aspects of occupant behaviour. Also, the most advanced published models for occupant presence (proposed by Wang and Yamaguchi) still neglect its time-dependence over a day and over a year.

Objectives

This article proposes such a set of stochastic models for the simulation of occupant presence and behaviour. Our aim is not to reproduce the exact behaviour of occupants but rather to make sure that each aspect of occupant behaviour that has an influence on a buildings' consumption of resources and production of waste is reproduced in a statistically reasonable way. This should be useful for the prediction of peak energy demand, the temporal profile of this demand as well as the comfort of the occupant and her/his possible acceptance of integrated passive systems.

RESEARCH METHODS

Procedure

The models developed can be applied to any type of occupants (given the corresponding inputs) as well as any number of buildings. Each building is broken down into "zones", the unit volume in which a fixed number of occupants are present and with which they interact. One zone would correspond to a flat in residential buildings or an office room in commercial buildings. The occupants of a zone are simulated independently.

The model of occupant presence is obviously the core model and produces an input for each of the behavioural models (see figure 1). The latter all use the time series of simulated presence (a sequence of zeros and ones at each time-step for each occupant of a zone) as an input. The behaviours considered are the opening of windows, the use of appliances consuming electricity and/or hot and cold water and the production of solid waste.[1] Measured data was used for the calibration and validation of the models as well as their continuous development. It was collected within the framework of the SUNtool project (Robinson et al. 2003, 2007). The aim of this EU funded project was to develop a software tool capable of simulating the resource flows of urban neighbourhoods. The set of stochastic models explained here were developed to be integrated within this tool.

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[1] An adaptation of the Lightswitch model for the use of blinds and lighting appliances has also been performed.

Model of occupant presence

We developed this model based on the hypotheses that each occupant's presence is independent from that of any other and that the state of an occupant's presence at a given time-step only depends on her/his state of presence at the previous time-step. This last condition naturally leads us to the use of Markov chains. But, while Yamaguchi considers the probability of transition (from one state of activity to another) to be time independent, we want to calculate this probability for each time step of a week. To do this we use the profiles of probability of presence that are typical inputs of building simulation tools (for example the diversity profiles mentioned earlier could be used for this).[2] We still lack some information to uniquely fix the probabilities of transition. This is done by introducing a new parameter that expresses the rate of movement in and out of the zone simulated and that we call the "mobility parameter". We can now simulate the typical periods of presence and absence that appear during one day; but what about days when the occupant does not appear at all? For this we add to our Markov chain model the simulation of periods of absence longer than one day (but not a weekend), to account for periods of external meetings, vacations or ill health.

With the parameter of mobility, the profile of presence and information on the periods of long absence, we are now capable, by using the inverse function method (IFM), of generating any number of time series of presence of any length of time. This output can be converted into metabolic heat gains injected into a zone but more it importantly serves as an input to all the models of occupant behaviour. We refer the reader to Page et al. (2007) for a detailed description of the model and results from its validation.

Model of use of appliances

We understand "appliance" to mean a group of appliances fulfilling the same function or participating in that function. For example a computer, a printer, a modem and a set of loud-speakers will be considered as a "computer appliance", with parameters covering the aspects of these individual appliances; a sink, a shower and a bath can be the various incarnations of a "body cleansing appliance". The model distinguishes four categories of appliances: those that have a (practically) constant consumption (such as a fridge) or a fixed profile of use and are independent of occupant presence, those switched ON by a user and therefore depend on her/his presence (e.g. washing-

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[2] These usually provide hourly values. We were able to calibrate the model with time-steps of 15 minutes. This higher resolution will be useful for the behavioural models of window opening, lighting and appliance use.

machine) and those switched ON and OFF by an occupant (e.g. shower, television). Appliances of the last two categories will be switched OFF when the period of use, determined according to the distribution of duration of use, comes to an end. Those of the latter category can also be switched OFF when the occupant using them leaves the zone. Finally a category "stuff" regroups appliances which are too small to be modeled individually but can be collectively significant. Before simulating the use of appliances it is necessary to determine:

- which appliances are to be found within each zone (what types of appliances and how many of each type),
- at what rate of electricity consumption (i.e. power) and water consumption (hot and cold) they will be used,
- for how long they will be used,
- what their standby power is and how liable the occupant is to leave the appliance in this state when not using it,
- and finally what the probability is that an occupant might switch an appliance ON for each time step of a week.

The values of these parameters are fixed in a pre-process phase, given the technical characteristics of the appliances installed and the more social characteristics such as the type of occupancy (commercial or residential – with family size given in this latter case) and behaviour regarding appliance use (e.g. appliances are switched OFF or left on standby). This preliminary part of the model determines the installed power within the zone; it is therefore the first step in reproducing the random resource consumption related to the occupant. As noted earlier, occupants' interactions with appliances depend on their presence. The time series for each occupant of the zone produced beforehand by the presence model will therefore serve as an input to this model. This covers the next cause of randomness within resource consumption, namely occupant presence.

Appliances functioning at constant power, others that follow a programmed schedule (hot water boiler) as well as "stuff" can also be considered in the pre-process phase: the former consume a fixed amount of water, electrical and thermal energy, while in the case of the latter two we generate consecutive sequences of respectively deterministic and stochastic duration of use and consumption rate. The sum of the three serves as an occupant-independent base load. Appliances that rely on occupants' presence to be switched ON are simulated in the processing phase. At each time step the model checks for each occupant whether (s)he wants to switch ON a type of appliance unused at the moment (one occupant only uses one appliance of a type, for example one TV when two are available). It does this by applying the IFM to the probability of switch ON

given by the probability profile for this time step of the week. When an appliance is switched ON the duration of use and power of use are deduced from the respective distributions thanks to the IFM. A counter allocated to the use of the appliance is decremented by one unit at each time step. An appliance is switched OFF when the counter is equal to 0, or when the occupant using the appliance leaves, in the case of appliances whose switching OFF necessitates the interaction of an occupant. Once OFF the appliance stays OFF for at least one time step. Certain appliances may be used collectively (a cooker for example) in which case the power will be related to the number of occupants using them.

At each time step the model calculates the total water consumption and waste water produced, the total electrical and thermal (from hot water) energy consumed and the resulting heat given off to the zone by all the appliances (electrical appliances ON or on standby, fraction of heat from appliances using hot water) and fraction of (grey) water recoverable from the waste water. From this we can also determine the load profile and rate of consumption of hot and cold water of the zone and therefore the distribution of its peaks.

Model of opening of windows

The model of opening of windows by the occupant is more behavioural than that of appliance use. Its randomness depends on the presence of the occupant, the physical stimuli causing her/him to open or close the window and the variability of occupants' tolerance towards these stimuli. Occupants open a window to ventilate a place when discomforted by the concentration of pollutants or to cool a zone when it is considered to be too hot; a window is closed when the indoor temperature is considered to be too low. At departure the occupant may decide to close the window or leave it open.

The occupants' levels of tolerance towards the concentration of pollutants and their level of discomfort when exposed to cold and hot indoor temperatures are based on well accepted studies (Fanger 1988, 1982). Each occupant is given a set-point of tolerance for each discomforting influence drawn from distributions proposed by Fanger. It is assumed that occupants are sensitive to pollutants only on arrival into a zone.

For this model we distinguish between the stimuli and associated interactions and the effects of these interactions. Concerning the latter an air exchange rate is calculated based on single-sided buoyancy driven ventilation. But since SUNtool's timestep is 60min a simplified thermal model with a timestep of 5min calculates a new temperature (due to the low heat capacity of air, large temperature changes may occur rapidly) which is communicated to the window interaction model. A time-weighted heat gain/loss is finally parsed to SUNtool. Due to lack of knowledge

of internal building layout in SUNtool, no exchange of air between zones of a building is considered.

Model for use of lighting appliances and blinds

The model for the use of lighting appliances and blinds has been directly adapted from the Lightswitch model proposed by Newsham (Newsham et al. 1995) and Reinhart (Reinhart 2004) to the specific needs of the SUNtool software. While their model of occupant use of lighting appliances is amongst the best available, the modeling of blinds needs further development (Robinson 2006).

Model of production of waste

A simplified model for the production of solid waste uses the output of the model of presence and statistics related to types of wastes (recyclable, organic, non-recyclable) to infer the weekly production of each type by the occupants of the simulated zone. The purpose of this is to support the modeling of the derivation of energy from waste in SUNtool.

RESULTS

Within this article we shall concentrate on the results provided by the models of occupant presence and use of appliances.

Model of presence

As this model works as an input to all behavioural models it is important that it be thoroughly validated. We did so by conceiving a list of indicators – properties of the output of the model that play an essential part as inputs to the behavioural models, such as:
- the "time of first arrival" and "time of last departure" that inform us of occupants' behaviour regarding blinds, lighting appliances and windows,
- the duration of "periods of absence" and of "periods of presence", whose importance Wang highlighted in the behaviour of occupants towards lighting appliances,
- the "cumulated presence over a day" or over a week are excellent indicators of the time an occupant *really* spends within a zone, and, when the former is compared with the "daily presence" (the difference between the time of first arrival and of last departure) this indicates the potential for saving electricity during occupants' short absences from the zone. By comparing the distribution of these indicators resulting from data measured in single person offices of the LESO building and from simulations with our model, we were able to assess how well the model reproduced these indicators.

These results are given and discussed in great detail in Page et al. (2007). However we would like to highlight two important features of the model with figures 2 and 3.The first shows the distribution of periods of presence and the second that of presence cumulated over a week. Monitored data is in green,

simulated values are in red and standard value(s) typically used in simulation tools are represented by vertical bar(s). Figure 2 proves the hypothesis that the duration of periods of presence cannot be considered to be inhomogeneous and shows how closely this model has come to reproducing the actual indicator, both in terms of dependence on time and dependence on the occupant simulated. Figure 3 shows how the presence of occupants is greatly overestimated by models so far. First of all occupants spend less time within an office than the 8 hours usually estimated due to them moving into and out of their office. But more importantly, occupants often leave their office for long periods of absence (lasting a fraction of a day, days or weeks) for various reasons such as work out of the office, sickness or vacation. The models of occupant presence proposed so far either neglect this absence or consider it in the best of cases by using fixed periods of vacation. However the figure clearly shows that these periods of absence vary greatly and absolutely need to be considered (which this model does in a convincing way).

Model of appliances

As our aim is to reproduce the stochastic behaviour of occupants regarding the appliances at their disposal, we have focused our attention on checking that, given the profiles of presence of each occupant and the appliances installed in the zone, we simulated correctly the use of appliances of categories 2 and 3 in terms of the resulting energy consumed and peaks of load produced. To do this we simultaneously collected the profiles of presence and electricity consumption[3] of the appliances within the zone as well as the zone's total consumption. This was done for 5 singly occupied offices (approx. 40 weeks of computer and lighting use with a 15min time step) and for 8 households (approx. 15 days of 6 most relevant appliances with a 2min time step). While the two office appliances measured typically function for long periods at low power, many household appliances are used for short periods at high power and therefore require the highest resolution possible.

The method of validation consisted in generating 100 simulations of the use of each appliance for each time unit (one day for residential data, one week for office data) with the measured presence during the time unit of interest as an input to the model. The parameters related to the appliance and its use by occupants are calibrated based on observations relating to the other time units. We then assessed the model based on its capability of producing realistic values of the following indicators: total energy consumed by the appliance during the time unit and

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[3] Unfortunately we did not have the needed data of water consumption and occupant presence to validate water-related appliances.

the 10th, 90th and 100th percentiles of its load profile; these give a good idea of the base load and peak load. Figure 4 shows the results from the cumulated profiles of a computer and a lighting appliance from an office.[4] The box-plots (top left) show, for each week simulated, the spread of the 100 simulations around the mean of the total energy consumed during that week; the measured value (green star) and the value predicted by using an adapted diversity profile (red cross) serve as comparisons. The top right graphic expresses the distance (absolute value of the difference divided by the value measured) between the measured value of total energy for each week and either the average of the simulations (blue star) or the value predicted by the diversity profile. The two bottom graphics show the distance for the 90th (left) and 100th (right) percentiles, giving an idea of how well the model (and the diversity profile) estimate the peak values taken on by the appliance. The box-plots show that although the diversity profile does well at estimating the total energy half of the time (25 of 42 weeks slightly better than the model) the model's estimation is never more than 12% worse off while still being a lot more reliable the rest of the time. 9 of the weeks correspond to periods of quasi null consumption (and typically complete absence of the occupant) but another 12 correspond to a variability in consumption that fixed profiles cannot predict (the last 11 red crosses lie above the y=1 axis). This observation is even more obvious for the prediction of peak loads: the threshold for peak loads, we fixed at 90%, is always better estimated by our model, as well as the maximum peak at 100%. This is quite convincing as diversity profiles are normalised thanks to the maximum peak value of the office over the whole period.

DISCUSSION

We have presented here an attempt to simulate occupant influences on resource flows within buildings. The novelty of this approach is the simple consideration that the presence of the occupant is a necessary condition for her/his interaction. This has led us to develop a core model of occupant presence whose output serves as an input to a family of stochastic behavioural models. An account of the detailed functioning and promising results of the model can be found in (Page et al 2007). This approach has admittedly been used in precedent studies but with the flaws we have discussed earlier, namely time-independent probabilities of transition, repetition of daily patterns and therefore neglecting long periods of absence. In overcoming these shortfalls we have tried to keep the inputs to the model as simple as possible by using inputs already common to simulation tools (such as profiles of probability of presence) and by helping the user

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[4] Comparison for residential data is under way.

assess new parameters (such as the parameter of mobility).

We have compared the stochastic model of appliance use to the latest method of diversity profiles in the case of an office building. While our model sometimes slightly overestimates and other times underestimates the weekly total energy and peaks it has proven itself capable of following the variability of the measured weekly loads, a feature that diversity profiles are incapable of providing. This is of particular importance in estimating peaks as these clearly vary from one week to the other.

The lack of inter-zonal flows of air and the adoption of Fanger's results for buildings that are not necessarily air-conditioned are obvious flaws of the model of window opening. Yet it proposes a simple algorithm based on well-established conclusions of the field of thermal comfort that can easily be modified to include more complex sub-models of fluid dynamics and human thermal comfort (Haldi and Robinson 2007).

CONCLUSION

As building standards improve, so the relative impact of occupants on resource use will increase. It thus seems inevitable that better models of their presence and interactions will be necessary. The set of models discussed in this article is a first attempt to simulate the multiple influences occupants can have on a building in terms of resource consumption and waste production. Their outputs will provide valuable information for the simulation of a single building or a group of buildings in the form of a time series of resources needed (electricity, hot and cold water) and waste (waste water and solid waste) produced by the building(s), but also of heat given off to the building(s) or evacuated from the building(s) in the case of ventilation. This shall be useful to building engineers and architects, but also to urban planners as tools for simulating and optimising urban resource flows are now becoming available.

Central to this set is the stochastic model of occupant presence. It has demonstrated its advantages over standard methods and can serve as an input to the behavioural models discussed here. It can also bring an added-value to tools already using simulations of occupant behaviour, such as Lightswitch, by providing them with more reliable inputs.

The stochastic models of occupant behaviour (regarding the use of appliances, the opening and closing of windows and the production of waste) complement this already stochastic input by representing the variety of occupant behaviours and their randomness over time. Of particular interest is the appliance model, which surpasses standard methods in determining the overall internal heat gains and predicting the peaks in resource demand. This will be of future use for the sizing and networking of local power and heat production.

REFERENCES

Abushakra B., Sreshthaputra A., Haberl J. and Claridge D.E. 2001. "Compilation of diversity factors and schedules for energy and cooling load calculations." ASHRAE Research Project 1093-RP, Energy Systems Laboratory, Texas A and M University (USA).

Bourgeois D., Reinhart C. and Macdonald I. 2006. "Adding advanced behavioural models in whole building energy simulation: A study on the total energy impact of manual and automated lighting control." Energy and Buildings 38: 814-823.

Fanger P.O. 1982. Thermal Comfort. Florida, USA, R.E. Kreiger.

Fanger P.O. 1988. "Introduction of the olf and decipol units to quantify air pollution perceived by human indoors and outdoors." Energy and Buildings 12: 1-6.

Fritsch R., Kohler A., Nygard-Ferguson M. and Scartezzini J.-L. 1990. "A Stochastic Model of User Behaviour Regarding Ventilation." Building and Environment 25 (2): 173-181.

Haldi F., Robinson D. 2007. "On the behaviour and adaptation of office occupants." Energy and Buildings (submitted).

Herkel S., Knapp U. and Pfafferott J. 2005. "A preliminary model of user behaviour regarding the manual control of windows in office buildings". Proceedings of the 9th International IBPSA Conference, Montréal, Canada.

Newsham G., Mahdavi A. and Beausoleil-Morrison I. 1995. "Lightswitch: a stochastic model for predicting office lighting energy consumption". Proceedings of Right Light Three, the 3rd European Conference on Energy Efficient Lighting, Newcastle-upon-Tyne, UK, pp 60-66.

Nicol J. F. 2001. "Characterising occupant behaviour in buildings: towards a stochastic model of occupant use of windows, lights, blinds, heaters and fans". Proceedings of the 7th International IBPSA Conference, Rio de Janeiro, Brazil.

Page J., Robinson D., Morel N. and Scartezzini J.-L. 2007. "A generalised stochastic model for the simulation of occupant presence." Energy and Buildings (in press).

Reinhart C. 2004. "Lightswitch-2002: a model for manual and automated control of electric lighting and blinds." Solar Energy 77: 15-28.

Robinson D., Stankovic S., Morel N., Deque F., Rylatt M., Kabele K., Manolakaki E., Nieminen J. 2003. "Integrated resource flow modelling of urban neighbourhoods: Project SUNtool. Proceedings of Building Simulation 2003, Eindhoven, The Netherlands.

Robinson D. 2006. "Some trends and research needs in energy and comfort prediction." Proceedings of Comfort and Energy Use in Buildings, Windsor, United Kingdom.

Robinson D., Campbell N., Gaiser W., Kabele K., Le-Mouel A., Morel N., Page J., Stankovic S., Stone A. 2007. "SUNtool - a new modelling paradigm for simulating and optimising urban sustainability." Solar Energy (in press)

Tanimoto J. and Hagishima A. 2005. "State transition probability for the Markov Model dealing with on/off cooling schedule in dwellings." Energy and Buildings 37: 181-187.

Wang D., Federspiel C. and Rubinstein F. 2005. "Modeling occupancy in single person offices." Energy and Buildings 37: 121-126.

Yamaguchi Y., Shimoda Y. and Mizuno M. 2003. "Development of district energy system simulation model based on detailed energy demand model." Proceedings of the 8th International IBPSA Conference, Eindhoven, The Netherlands.
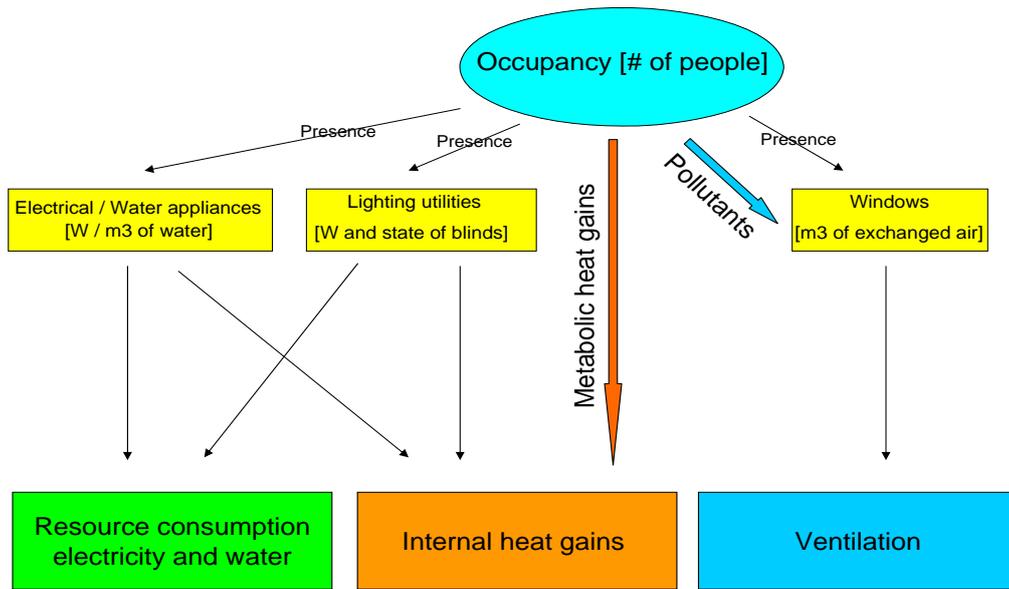
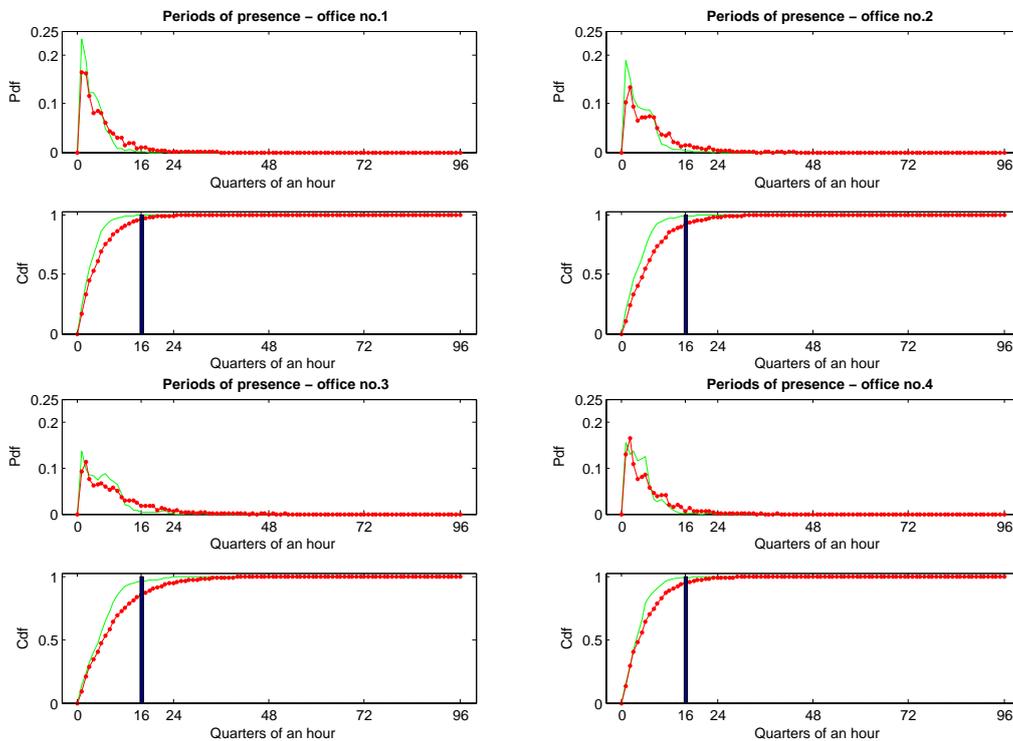Figure 1: *Outputs of the occupancy model and their later use by stochastic models of occupants' behaviour.*

Figure 2: *Comparison, between the monitored data (green solid line) and the simulated time series (dotted red line), of the PDFs (probability density functions) and CDFs (cumulative distribution functions) of "periods of presence" for four private offices. The blue histograms correspond to the repeated use of a standard fixed profile.*
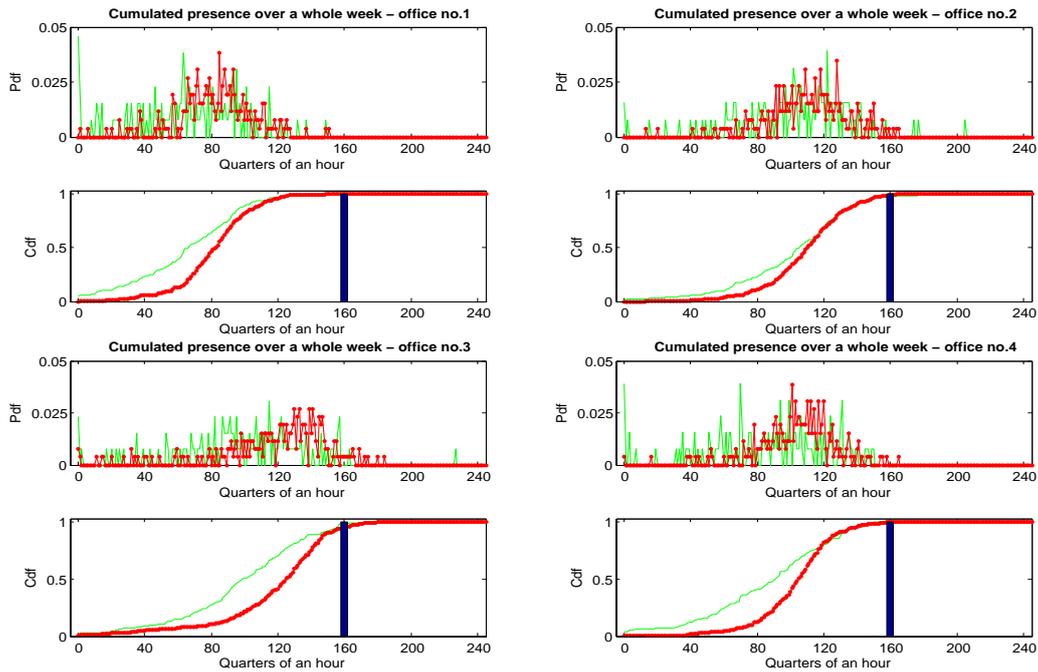
Figure 3: *Comparison of the "cumulated presence" over one full week for four private offices.*
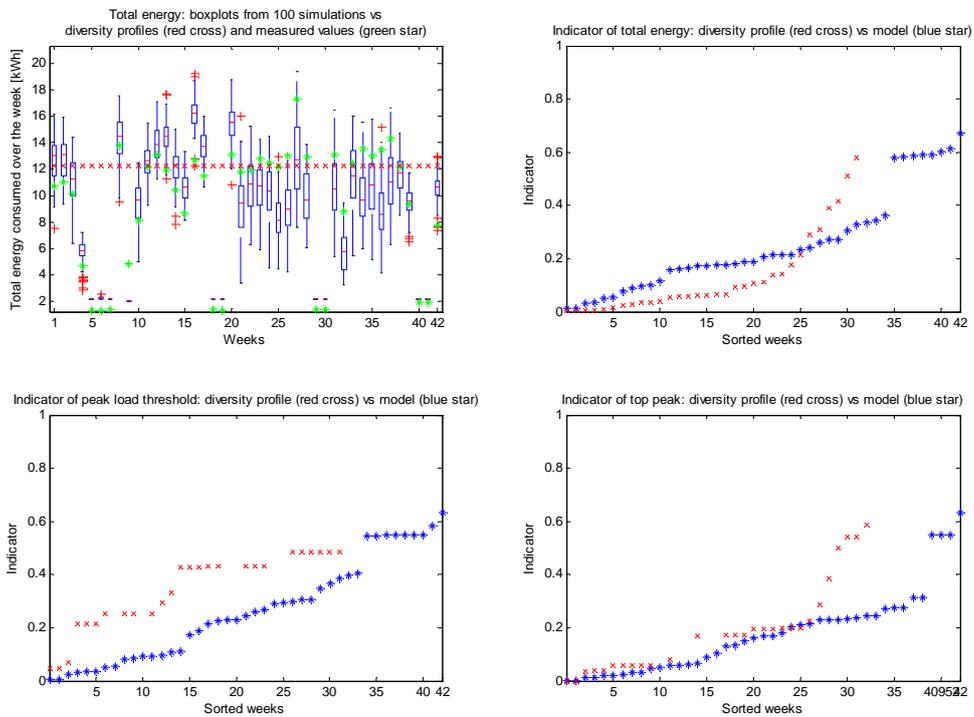

Figure 4: *Comparison of simulated   weeks with measured results and values predicted by the diversity profiles: top left – box-plots of total energy with measured values (green star) and values predicted by diversity profiles (red cross); clockwise from top right – indicators of total energy, top peak(100th percentile) and peak threshold (90th percentile) for simulated values (blue star) and values predicted by diversity profiles (red cross).*