Appraising the effects of window opening behaviour in an office building in different climates

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Abstract

There is extensive pressure on sustainable buildings to deliver energy efficiency, but in practice, designs often fail to achieve the expected level of in-use energy consumption. One of the main factors behind this discrepancy between designed and real total energy use in buildings is the window opening behaviour. Towards nearly zero energy building (NZEB), building performance simulation is being increasingly deployed beyond the building design phase.

With the aim to investigate how the climate affects the probabilistic model of window behaviour, the case study is simulated in different locations, i.e. Continental (Turin) and Mediterranean (Athens). Moreover, each simulated model refers to three comfort category heating and cooling set point conditions (Category I, II, III) as defined in Standard EN 15251:2006. Comparing the results, the influence of window behaviour on energy consumption in different climates generates energetically different outcomes. The present study highlights the importance of users' interaction with window control systems in order to design sustainable and energy-efficient office buildings in a more realistic way.

1. Introduction

Energy reduction in the built environment is an essential issue; particularly, an improved building design during the early design phase is instrumental in the efforts of reducing energy (Clarke, 2001). Therefore, it is required to understand the factors that influence the energy consumption in a building.

Measured real energy use of buildings demonstrates large differences from predicted ones, even between buildings with the same functions but located in different climates.

Following the literature, human behaviour can be considered one of the key driving factors in changes in energy consumption; especially it has been shown to have a large impact on heating, cooling, ventilation demand and lighting (Page, 2008). Accordingly, several stochastic models have been expanded to model occupant presence and interaction with the building system. Based on measurements in office rooms without mechanical ventilation, a Markov chain model for actions on windows, with the outside temperature as a driving variable, was propounded by Fritsch et al. (1990). Reinhart et al. (2004) defined occupant presence in lighting software by employing a simplified stochastic model divided into sub-models based on users' arrival and departure. Wang et al. (2005) applied Poisson distributions with the aim to generate daily occupancy profile in a single-occupied office. Mahdavi et al. (2008) inquired the possibilities of identifying general patterns of user control behaviour as a function of indoor and outdoor environmental parameters such as illuminance and irradiance.

Since energy building simulation tools are used to estimate the future performance of the building, dissimilar input parameters may introduce uncertainties. Besides, it is assumed that user behaviour is one of the most important input parameters influencing the results of building energy simulations. Accordingly, it is fundamental deploying a model that considers the randomness of human behaviour through a probabilistic approach with the purpose of predicting the actual energy demand of the building. However, it is difficult to completely identify the influences of

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occupant behaviour and activities through simulation owing to users' behaviour diversity and complexity; while most current simulation tools can only imitate behaviour patterns in a strict way, occupants' behaviour is the result of a continuous combination of several factors crossing different disciplines (Fabi et al., 2013) and therefore is still an object of investigation.

Rijal et al. (2007), Haldi and Robinson (2009), Herkel et al. (2008), Yun and Steemers (2008) have been pioneering a method to represent occupant interaction with buildings using stochastic models which later can be used to create window control strategies. The general trend has been to infer the probability of the window state as a function of indoor and outdoor temperature, while other studies have investigated the probability of opening a window (change from one state to another) as a function of indoor temperature (Yun and Steemers ,2008, Yun et al., 2008).

Actually, two important parameters influencing energy consumption in buildings are indoor temperature and air change rate, which are directly linked to the occupant's usage of the window. According to studies conducted by Raja et al. (2001), windows had the biggest effect on indoor climate of all available controls. Consequently, it is crucial to take window opening behaviour into consideration.

In office buildings, fully automatic controlled solutions are becoming progressively more common since they can simultaneously enhance individual comfort and use a reduced amount of energy. However, these systems frequently offer limited user autonomy, since user satisfaction and freedom are strongly connected. Moreover, the ability to control their own indoor environment contributes significantly to their satisfaction and general perception of the indoor climate (Wagner et al., 2007).

With these premises, the current paper investigated how different occupant-related models, assuming a behavioural pattern of window-opening, can affect the energy use of an office building. Precisely, a dynamic numeric simulation application was deployed to compare a model based on a fixed schedule with probabilistic models, at first in a Continental (Torabi Moghadam et al., 2014) and then in Mediterranean weather, in order to analyse the discrepancy between predicted and simulated energy performance in different climates.

2. Simulating Window Behaviour

2.1 Case study

An office building with fifteen cellular office spaces was selected as a case study to evaluate the influence of window operation on thermal simulation results. The floor plan of the basic building model was designed in the framework of the Developing Architectural Education in Response to Climate Change program (DARC program, Polito).

The case study building consists of 5 floors (see Figure 1): each of them has a surface area of about 1400 m^2. As regards the orientation of the building, the two main façades are oriented south-west and north-east. The floor-to-floor height is 3.5 m; hence the building's total height is 19.3 m.

For more exhaustive energy or load calculations in each office room, a more detailed zoning is required. Therefore, each office cell is modelled as a single zone (see Figure 2).

The modelling assumptions for the building use are listed in Table 1. Simulations were carried out for 3 different categories pertaining to the heating and cooling set points of the building's control systems as relevant to the office spaces. These categories are defined in Standard EN 15251:2006 and included in Table 2.

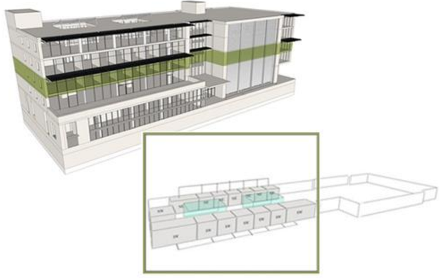


Fig. 1 – 3D model of the office building and modeled zones

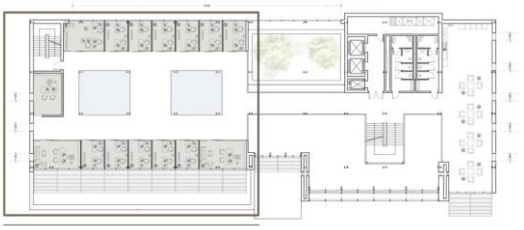


Fig. 2 – Building standard floor plan

Table 1 – Modelling assumptions for building use

Modelling assumptions	Offices
Installed lighting power	10 W/m^2
Occupancy	8:00–18:00
Air change rate (3)	1 h^{-1}
Equipment (occupied period) / (unoccupied period)	15 W/m^2 / 5% of total emitted heat

Table 2 – Standard EN 15251:2006. Recommended temperature ranges for the internal temperatures in office buildings.

Type of building	Cat	Operative temperatures [°C]		ACH [h^{-1}]
		Min. for heating (~1,0 clo)	Max. for cooling (~0,5 clo)	
Office rooms	I	21	25.5	1
	II	20	26	
	III	19	27	

2.2 Methodology

The main purpose of the research was to understand the influence of the climate on probabilistic windows' opening and closing behaviour by performing simulations in two different climate zones (Turin and Athens), taking 2012 as a typical meteorological year (TMY).

Since many office buildings are provided with a hybrid ventilation system, in the current study, in the probabilistic scenario, every office room was equipped with a combination of mechanical ventilation and operable windows. Furthermore, two dissimilar window controls were compared in order to highlight differences in window behaviour impact on the energy consumption discrepancy, during the design phase.

First, the windows were scheduled to be constantly closed and fresh air is supplied exclusively via the mechanical ventilation system (1h^{-1}); this kind of control is called "*deterministic*" by the authors. Secondly, the windows were simulated to be opened in accordance with the stochastic model of Haldi and Robinson (2009) implemented in the simulation tool used in the current study (IDA ICE, 4.21.); authors defined this control type on windows as "*probabilistic*". Afterward, the case study is simulated in different locations, i.e. Continental (Turin) and Mediterranean (Athens), using the relative weather data, with the aim to investigate how the different climates affect the office building's energy performance.

For each thermal zone, in every selected climate - Turin and Athens - the algorithm describing users' interactions with windows was implemented in the dynamic simulation tool. Simulations were run 30 times for three comfort categories (see table 2) setting all fixed inputs and one occupant, to understand the impact of the windows' behaviour on the investigated performance indicators.

Since most window openings can be associated with the arrival of an occupant in the office, the probabilities of opening and closing windows were separately estimated in three different sub-models representing the situations of occupants' arrival, departure and during their presence (Herkel et al., 2008). This dynamic method can account for the real adaptive processes of occupants by performing for each of those sub-models a logistic regression which takes into account the most relevant environmental parameters (indoor and outdoor temperature, prior absence duration and rainfall).

In the following research an experimental approach into subsequent scenarios has been developed which was based on two steps, where two window controls were defined: firstly the study has treated office energy performance as automatically performed in the design stage of energy dynamic simulation software; secondly, the model that assumes a probabilistic interaction between users and window opening and closing has been built.

The work focuses on the relationship of window opening behaviour, and the model describing the use of shading system is not applied to the reference building.

Table 3 – Regression coefficients of the probability functions of the window submodels. Previous absence, occurrence of rain and next absence are binary variables.

		Physical driving variables						
		T_{in} [°C]	T_{out} [°C]	Previous absence [-]	Rain [-]	Ongoing presence [min]	$T_{out,daily\ mean}$ [°C]	Next absence [-]
Sub models	a	b_{Tin}	b_{Tout}	b_{abs_pr}	b_{rain}	b_{Tpres}	$b_{Tout,dm}$	b_{abs_next}
Opening at arrival	-13.7	0.308	0.0395	1.826	-0.43	0	0	0
Closing at arrival	3.95	-0.286	-0.05	0	0	0	0	0
Intermediate opening	-11.78	0,263	0.0394	0	-0.336	-0.0009	0	0
Intermediate closing	-4.14	0.026	-0.0625	0	0	0	0	0
Opening at departure	-8.72	0	0	0	0	0	0.1352	0.85
Closing at departure	-8.68	0.222	-0.0936	0	0	0	0	1.534

3. Discussion and results

The subsequent graphs (Figures 4, 5 and 6) provide a summary of simulated air change rate, heating loads and cooling loads for the above mentioned two scenarios (“deterministic” and “probabilistic”). Moreover, table 4 describes the variation of the results by the fluctuating categories of comfort.

Especially, each performance indicator is presented comparing the Turin and Athens climates in order to corroborate the impact of different climates on energy consumption and window opening and to investigate for each control, as well as each simulation set, what influence the climate would have on the fluctuation of the result, due to the changes in behaviour of the window. The investigations were carried out with the main goal of identifying the influence of climate on the alteration in results between the deterministic and probabilistic approach to the building energy simulation.

Great variations in energy consumption emerged from the data elaboration, switching from a deterministic to a probabilistic approach to window opening (Figure 4, 5 and 6), for both the climate zones. Actually, using a deterministic approach, the windows are always supposed to be closed according to the fixed schedule, while the stochastic model calculates the probability of a window being opened or closed without been driven by physical thresholds.

In particular, in a hybrid ventilated building the energy use increases because of more frequent occupant-window interactions. In other words, if the opportunity to open the window is given, occupants tend to open it more often than expected; accordingly the average values coming from the simulation sets are higher than the hygienic mechanical ventilation of the deterministic model, for both climate zones (i.e. maximum variation in Turin: 230%; maximum variation in Athens: 440%).

Figure 4 shows the change on air change rate moving the simulation to different climates. The warmer climate presents a higher frequency of window opening of 69.5% compared to the colder climate. Specifically, as it can be seen in Table 4, in Turin the probabilistic model provides air change rate predictions closer to the ones coming from the standard model (i.e. maximum $ACH_{CatIIITurin}$ = 4.81 h^{-1} in summer season), while in Athens the gap between results is more significant (i.e. maximum $ACH_{CatIIAthens}$ = 6.99 h^{-1}, during the summer, instead of 1 h^{-1} of the hygienic mechanical ventilation).

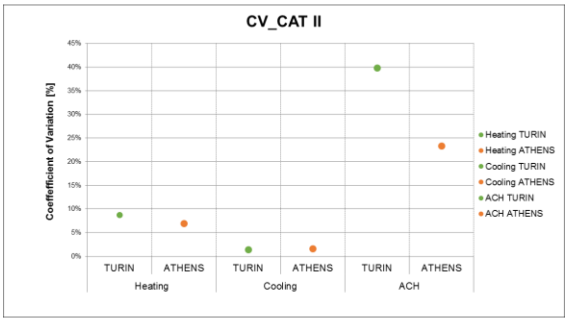
Note that the ACH is calculated by dividing the volumetric flow rate of air with the space volume of the rooms.

As a result, in models using a probabilistic algorithm for the window opening, the higher energy use for heating is in Turin with a discrepancy of 87.8% with respect to Athens (Figure 5). Conversely, the higher energy use for cooling is in Athens with a gap of 57.6% compared to Turin (Figure 6).

The variation of the results is a consequence of the influence of the climate on this probabilistic model. Specifically, the effect of climate on mean values of heating and cooling energy consumption and air change rate are different in the two climate conditions. Simulated models in Athens always show the maximum cooling energy use and air change rate and the lowest heating energy consumption; while in Turin they have the highest energy use for heating in all scenarios and the lowest air change rate and cooling energy consumption.

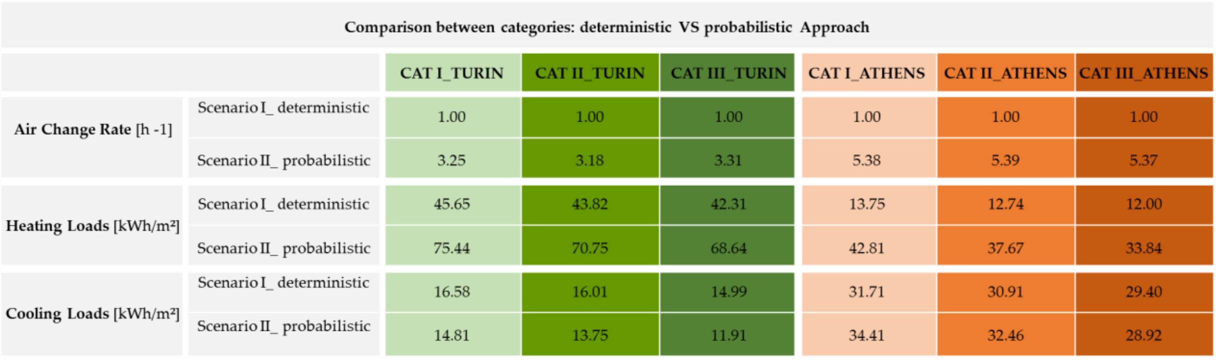
Once the influence of probabilistic control on energy demand is evaluated, the fluctuation of results within the same set of simulation is analyzed for the entire building using the Coefficient of Variation (CV). In probability theory and statistics, this indicator is a normalized measure of dispersion of a probability distribution or frequency distribution and it is defined as the ratio of the standard deviation to the mean. Therefore we used it to quantify the sensitivity of the performance indicator respect to changes in simulations. However, it can be seen that the two climate zones have similar values of CV, with the only exception of the air change rate in which Turin is about 40%, while Athens amounts to 25% (Figure 3).

Fig. 3 – CV values for annual heating load, cooling load and air change rate (Scenario II)



Once this analysis of the results is completed, it seems appropriate to ask whether users behave exactly the same way within a building. What if active or passive users will be simulated in Athens and Turin? An interesting development in the current research could be to investigate the influence of different types of users on the predicted energy consumption, in different climate zones.

Table 4 – Fluctuation of the results in the air change rate, heating load and cooling load calculations between different comfort categories



Comparison between categories: deterministic VS probabilistic Approach							
		CAT I_TURIN	CAT II_TURIN	CAT III_TURIN	CAT I_ATHENS	CAT II_ATHENS	CAT III_ATHENS
Air Change Rate [h -1]	Scenario I_ deterministic	1.00	1.00	1.00	1.00	1.00	1.00
	Scenario II_ probabilistic	3.25	3.18	3.31	5.38	5.39	5.37
Heating Loads [kWh/m²]	Scenario I_ deterministic	45.65	43.82	42.31	13.75	12.74	12.00
	Scenario II_ probabilistic	75.44	70.75	68.64	42.81	37.67	33.84
Cooling Loads [kWh/m²]	Scenario I_ deterministic	16.58	16.01	14.99	31.71	30.91	29.40
	Scenario II_ probabilistic	14.81	13.75	11.91	34.41	32.46	28.92

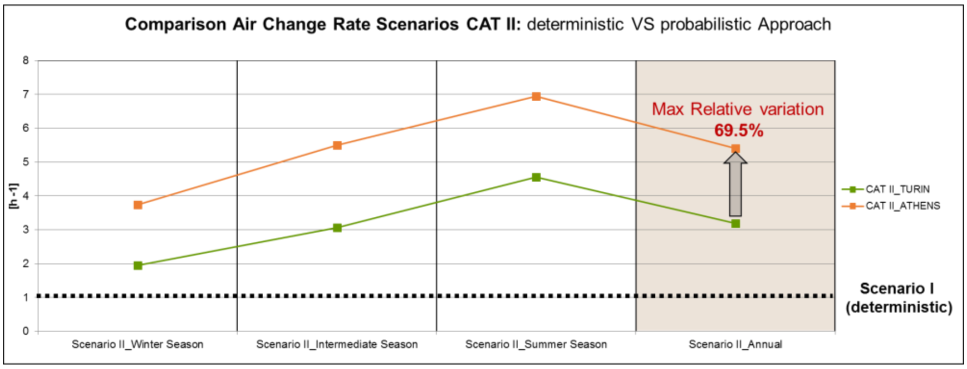


Fig. 4 – Comparison Air change rate scenarios of Cat II

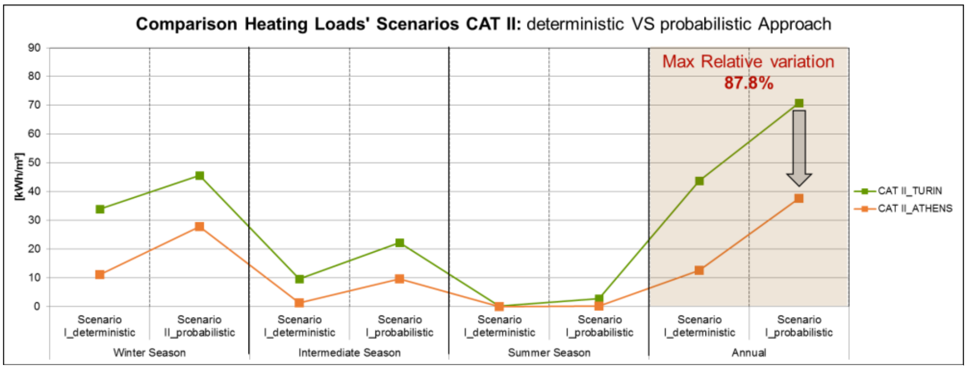


Fig. 5 – Comparison heating loads' scenarios of Cat II

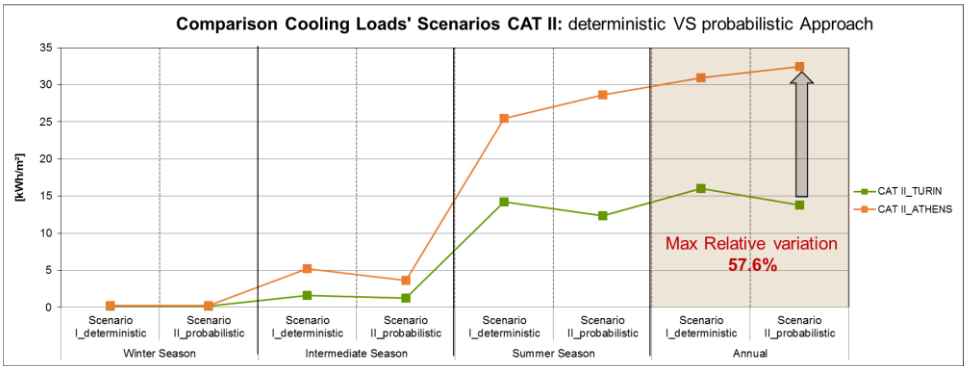


Fig. 6 – Comparison cooling loads' scenarios of Cat II

4. Conclusion

This paper aimed at highlighting the gap between two approaches of simulation, deterministic (with occupants' schedules fixed and always repeatable) and probabilistic (defined by a stochastic schedule of the building occupants). The huge gap often resulting between the predicted and the actual heating and cooling demands relies on the actions that building occupants perform in the indoor environment. The two approaches to simulate the occupants' activities, in an office building are simulated in different climates, through the implementation of a behavioural model taken from the literature, in a building energy dynamic simulation tool. Using a stochastic model, the use of the window is not predictable with certainty, but it is linked to the behaviour of the occupants. Accordingly, results show different energy outcomes between different control systems, in different climate locations.

In both climate locations, in winter the heating system has to compensate for the higher heat loss due to a more frequent interaction with windows leading to an increase of heating delivered energy.

This discrepancy is particularly more pronounced in Athens (e.g. from 12.74 to 37.67, that is + 196%), where the users, because of the warmer climate, tend to open the windows more frequently than in Turin (e.g. from 43.82 to 70.75, that is + 61%).

Conversely, in summer, the probabilistic model seems to have a lesser but positive influence, but only in the Continental climate of Turin since operations on windows seem to support the system to cool down the building reducing the expected cooling consumption (e.g. from 16.01 kWh/m^2 to 13.75 kWh/m^2, with a decrease of 14%, see table 4). The same notion was not valid for Athens (e.g. from 30.91 kWh/m^2 to 32.46 kWh/m^2, with an increase of 5%, see table 4), probably because of the high temperatures of the Mediterranean weather. As a matter of fact, in warmer climates naturally ventilated buildings tend to become overheated during summer periods and consequently users tend to open windows more frequently. This interaction necessarily leads to an increase in ventilation losses and hence cooling delivered energy.

Based on that, there is a difference in heating and cooling loads of fixed control versus manual, and it is necessary to clarify this discrepancy with further more detailed studies. Further research will identify different types of users (active and passive), analysing how they affect the predicted energy consumption in office buildings.

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