Ventilative cooling effectiveness in office buildings: a parametrical simulation

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ABSTRACT

Controlled Natural Ventilation (CNV) is one of the potential most effective passive cooling technique to reduce cooling needs of buildings in temperate-hot climate zones. However, a correct balance amid internal heat capacity, thermal insulation, and net opening area is important to achieve optimal results. The present paper shows results from an original simulation process carried out within the Course "ICT in building design" of the Master degree programme ICT4SS (ICT for smart societies) at the Politecnico di Torino. An office two-zone unit in Turin was simulated for fixed values of thermal insulation and internal heat capacity and increasing progressively external net opening area. Dynamic energy simulation was conducted for the cooling season period (May 1st ÷ September 30th) using Design Builder. The .idf output files were then used for the regression analysis, carried out by developing a Python script to allow for running the iterative process. A noise level related to a possible variation of the number of occupants was calculated through the Gaussian method. Results show that, while the internal heat capacity does not have a significant impact, thermal insulation could have a counterintuitive effect, i.e., the decrease of cooling energy with increasing opening area is less for the configuration with low U_{value} than the for the one with high U_{value} , above 20% of net opening area.

KEYWORDS

Ventilative cooling, Simulation, thermal insulation, internal heat capacity

1 INTRODUCTION

The need for reducing worldwide oil-based energy consumptions and correlated GHG is of paramount importance, as was discussed during the United Nations Climate Change Conference (COP 21) held in Paris in 2015.

The building sector alone is responsible of about 40% of the total primary energy consumptions, mainly related to space heating, cooling and ventilation, and electricity for domestic and office appliances [Orme, 2001; Cuce & Riffat, 2016]. Policies and regulations at European level have been adopted so far in order to reduce energy demand in buildings, e.g. Directive 2010/31/EU – EPBD recast. In spite of this, energy consumption for space cooling has been growing considerably due to several causes including climate changes and increase in indoor thermal comfort expectations [Santamouris, 2007]. This consumption trend has been only partially counterbalanced by an increase of the Energy Efficiency Ratio of the mostly applied space cooling systems [Santamouris, 2016]. The number of installed cooling units is, in fact, growing fast in both industrialised, and developing countries [Chiesa et al., 2017].

The increase in the number of mechanical cooling units suggests that alternative solutions are essentials. Among these alternatives, passive-dissipative-cooling systems are a valid alternative to reduce sol-air temperature peaks in buildings [Chiesa, Grosso, 2016].
The most general and easy applicable air-sink dissipative technique is the Controlled Natural Ventilation (CNV), i.e., a system by which envelope openings are controlled by temperature sensor-linked devices thus increasing or decreasing the amount of airflow rate, both wind-driven and buoyancy-driven, crossing a building space according to indoor-outdoor temperature difference and the indoor comfort upper limit [Heiselberg, 2018; Kolokotroni & Heiselberg, 2015]. The CNV effectiveness in reducing the energy cooling demand is also a function of the envelope U_{value} and the Internal Heat Capacity (IHC) of the considered building.
In this paper, the cooling energy demand in an office is simulated by an iterative process, whereby the airflow rate varies as a function of window opening percentage and results of energy loads are determined for different U_{values} and IHC.

2 METHODOLOGY

The work here presented was carried out by using as the software *Design Builder* to run a simulation of the energy demand (dependent variable Q) in a free-floating office module as a function of windows' opening, insulation level (U_{value}), and Internal Heat Capacity (IHC) as independent variables. The reference cooling period was May 1st through September 30th, with the climate of the City of Turin (Lat. 45°N, Long 7.5°E). The input data were then extracted on the form of an *.idf* file, which was used in a Python script developed on purpose to run iterative simulations by changing the parameters involved and calling the *EnergyPlus* engine. In this script, a Gaussian random noise with standard deviation equal to 2 was added to take the variation of office occupancy into account.

2.1 Model of the reference building

The reference module run in Design Builder is a generic middle section of an x storey linear office building, whose main façades are exposed to South and North (see figure 1a). It is composed of three blocks, representing: blocks 1, a typical medium floor; block 2, the top floor; block 3, a clerestory on the roof for stack ventilation. Blocks 1 and 2 have the same layout (see figure 1b), composed of two rooms separated by a corridor. Each room has an external wall with a window and a vent, one North and the other South, oriented. The other envelope surfaces are: two adiabatic walls; one adiabatic floor slab; one external roof slab; and the partition towards the corridor. Block 3 is just a technical volume with openings on the top of the block 2 in correspondence of the corridor, with a hollowed floor to allow for stack ventilation.

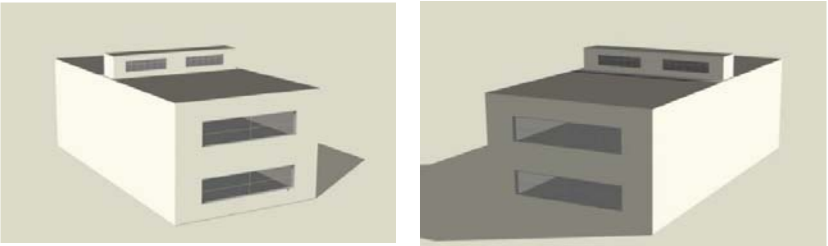

Fig.1a. Perspective representation of the office-building module used in the analyses

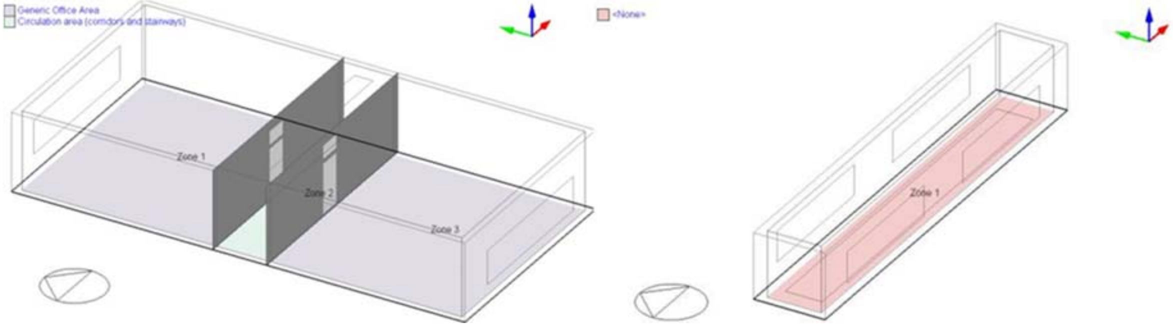

Fig.1b. Axonometric representation of the indoor distribution of the office space (left) and the clerestory (right)

2.2 Scenarios for the thermal input parameters

Six scenarios were considered for the independent variables U_{value} and *IHC*, as input parameters of the simulation. These scenarios were defined by combining their values within the following ranges: 3 levels of U_{values}; 2 values of *IHC*, representing low and high inertia. The U_{values} was defined by changing the thickness of the insulation layer (EPS expanded polystyrene) and the glazing type. The IHC was defined by changing the density of the concrete used for walls, floor, and roof slabs.

The scenarios are the following:

1st Scenario: high U_{value} (2,4 W/m^{2}K) and low *IHC* (40 kJ/m^{2}K). Insulation layer thickness of the walls: 0.0001 m; insulation layer thickness of the roof: 0.0003 m; and 3 mm-thick window single glazing. Concrete density = 400 kg/m^3.

2nd Scenario: medium U_{value} (0,24 W/m^{2}K) and Low *IHC* (40 kJ/m^{2}K). Insulation layer thickness of the walls: 0.1314 m; insulation layer thickness of the roof: 0.1316 m; and 3/13/3 mm-thick window double glazing with Argon. Concrete density = 400 kg/m^3.

3rd Scenario: low U_{value} (0,1 W/m^{2}K) and low *IHC* (40 kJ/m^{2}K). Insulation layer thickness of the walls: 0.3355 m; insulation layer thickness of the roof: 0.3358 m; and 3/13/3/13/3 mm-thick window triple glazing with Argon. Concrete density = 400 kg/m^3.

4th Scenario: high U_{value} (2,4 W/m^{2}K) and high *IHC* (180 kJ/m^2 K). Insulation layer thickness of the walls: 0.0001 m; insulation layer thickness of the roof: 0.0003 m; and 3 mm-thick window single glazing. Concrete density =1800 kg/m^3.

5th Scenario: medium U_{value} (0,24 W/m^{2}K) and high *IHC* (180 kJ/m^{2}K). Insulation layer thickness of the walls: 0.1314 m; insulation layer thickness of the roof: 0.1316 m; and 3/13/3 mm-thick window double glazing with Argon. Concrete density =1800 kg/m^3.

6th Scenario: low U_{value} (0,1 W/m^{2}K) and high *IHC* (180 kJ/m^{2}K). Insulation layer thickness of the walls: 0.3355 m; insulation layer thickness of the roof: 0.3358 m; and 3/13/3/13/3 mm-thick window triple glazing with Argon. Concrete density =1800 kg/m^3.

The parameters related to U_{value} are synthesised in Table 1. The one for *IHC*, in table 2.

Table 1. Values of the thickness of walls, roof, and glazing of windows.

U value	**High**	**Medium**	**Low**
Thickness wall (m)	0.0001	0.1314	0.3355
Thickness roof (m)	0.0003	0.1316	0.3358
Glazing windows	Single	Double with argon	Triple with argon

Table 2. Values of the density of the concrete.

IHC value	**Medium**	**Low**
Density concrete (kg/m^3)	1800	400

2.3 Simulation for modelling energy as a function of airflow rate

A simulation in *Design Builder* on the reference module described in § 2.1 was carried for each of the scenarios indicated in § 2.2 in order to obtain the cooling energy demand as a function of natural airflow rate, which is in turn dependent on the percentage of window net opening area. The input data of each scenario were exported from *Design Builder* as a *.idf* files, which were used as an extension of *Energy Plus*, the *DB* energy calculation engine, in order to iterate the simulation for various values of net opening area, hence, of airflow rate.
This iterative process was done by developing a python code, in which the *.idf* file is loaded in and the energy simulation is performed by *Energy Plus*. In the same script, a Gaussian random noise with standard deviation equal to 2 was added to take the occupancy of the zones in the office in to account.
The script was developed to run a loop of simulations by varying the window opening percentage from 0 to 100%. The loop was run two times in order to obtain two sets of data, one to train the model and the other to test its quality. The training data is composed of 40 different opening values, while the test data, 20.

A regression technique, also implemented in Python, was applied to the results from the simulation on the training data in order to find the best fit for the cooling energy demand (Q) as a function of the percentage of window opening, according to the following linear correlation amid input variables:

$$y\,(x, w) = w_0 + w_1 x_1 + \ldots + w_D\, x_D \tag{1}$$

where:
y = target variable (cooling energy demand);
w = weight;
x = input variable (window opening).

The goal was to calculate the weights w in order to minimize the square error between $\boldsymbol{y}$ and $\boldsymbol{X}_{\mathrm{w}}$ and obtaining the estimated values of w, which is given by:

$$\hat{\boldsymbol{w}} = [\boldsymbol{X}^T \boldsymbol{X}]^{-1} \boldsymbol{X}^T \boldsymbol{y} \tag{2}$$

The smallest error between target and prediction, while avoiding over-fitting was found by a sixth-degree polynomial function as the following:

$$\mathrm{y}(x, w) \;= w_0 + w_1 x_1 + w_2 x_2{}^2 + w_3 x_3{}^3 + \; w_4 x_4{}^4 + w_5 x_5{}^5 + w_6 x_6{}^6 \tag{3}$$

This correlation was tested against the test data to verify that the predicted cooling energy demand were close to the simulation results.

3 RESULTS

The values of the parameters in equation (3) for the different scenarios are shown in Table 3. In the following sections, the results of simulations and iterations are presented both by graphs and in tables, showing values of *Q* as a function of opening percentage.

Table 3. Values of the parameters in equation (3) for the different scenarios

	Parameters						
Scenarios	W_0	W_1	W_2	W_3	W_4	W_5	W_6
High U-value/Low IHC	44.65	-37.45	-305.92	1505.78	-2768.86	2328.72	-743.71
Medium U-value/Low IHC	52.20	-47.74	-471.25	1829.83	-2705.24	1841.10	-480.79
Low U-value/Low IHC	52.07	-38.13	-576.01	2140.18	-3126.31	2116.12	-550.87
High U-value/High IHC	45.05	-28.90	-399.50	1821.20	-3251.48	2666.99	-830.37
Medium U-value/High IHC	51.51	-27.31	-654.59	2486.07	-3803.51	2703.75	-737.98
Low U-value/High IHC	51.56	-46.66	-473.43	1714.94	-2306.92	1377.06	-299.52

3.1 Simulation output data: *Q* as a function of windows' openings

The testing data – points representing opening percentages randomly selected for each 10% step and a fitting curves – are shown in figures 2 and 3, for the scenarios with high and low IHC, respectively. Selected *Q* values for 5%, 50%, and 80% of opening are shown in tables 4 and 5, respectively.

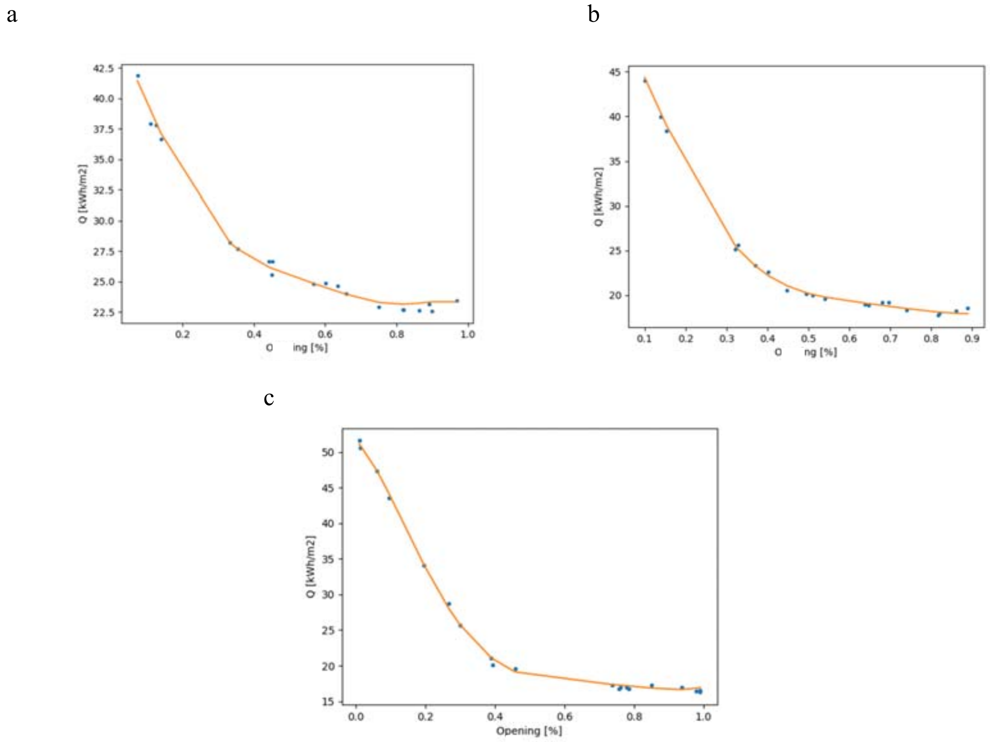

Fig. 2. (a) High *U*-High *IHC*; (b) Medium *U*-High *IHC*; (b) Low *U*-High *IHC*

Table 4. Q values for different U and high *IHC*.

U_{value}	Q (5% opening) [kWh/m^2]	Q (50% opening) [kWh/m^2]	Q (80% opening) [kWh/m^2]
High	42.81	25.52	23.14
Medium	48.79	20.20	18.18
Low	48.24	18.41	17.09

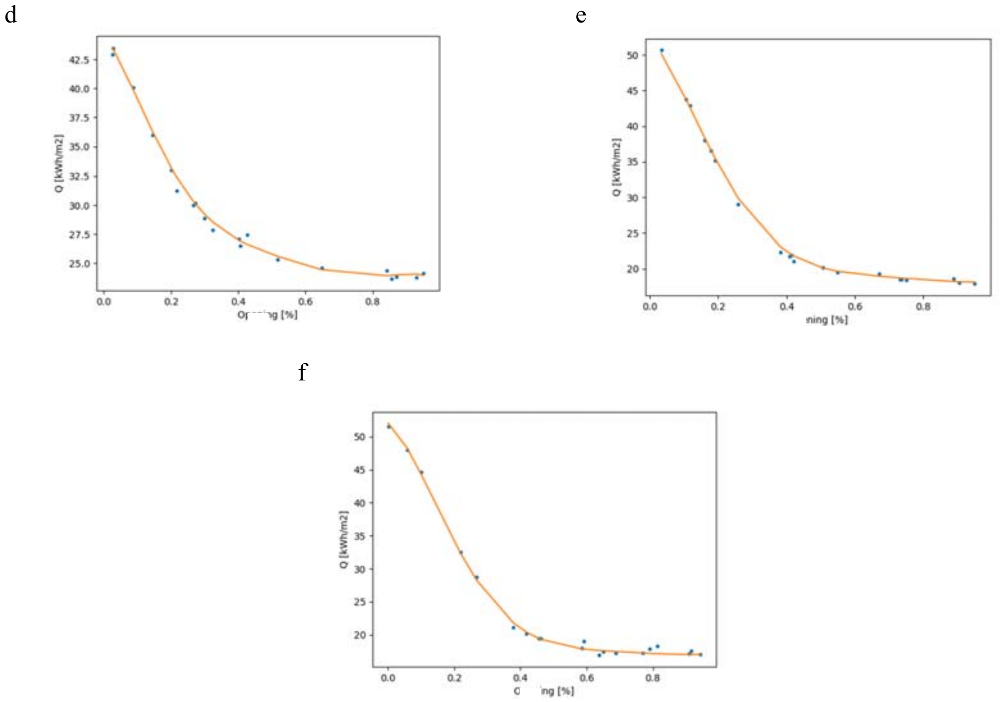

Fig.3. (d) High *U*- Low *IHC*; (e) Medium *U*- Low *IHC*; (f) Low *U* – Low *IHC*

Table 5. Q values for different U and low *IHC*

U_{value}	Q (5% opening) [kWh/m^2]	Q (50% opening) [kWh/m^2]	Q (80% opening) [kWh/m^2]
High	42.18	25.76	23.85
Medium	48.85	20.19	18.46
Low	48.97	18.65	17.16

As figures 2 and 3 show, for a given value of U and *IHC*, Q always decreases with increasing opening percentage. This is reasonable, since an increasing airflow rate with inlet of ambient air at a temperature suitable for cooling leads at a reduction of the cooling energy needs. However, tables 4 and 5 show that Q as a function of U_{value} increases for the lowest opening percentage (5%), while decreases for the other two values (50% and 80%).

This is due to the prevalent indoor-generated cooling load in the period and location of the case study under investigation. With a low U_{value}, i.e., with a high envelope insulation level, the heat generated inside the office space is trapped within the confined volume and the low airflow rate is not enough to dissipate such a heat.

3.2 Fitting curves of *Q* as a function of windows opening

The data resulting from simulation and iteration as shown in § 3.1 were fit by equation (3). The resulting fitting curve of *Q* as a function of windows' opening in the case of high *IHC* is shown in figure 4, while the curves of the same function for all 6 scenarios are shown in figure 5.

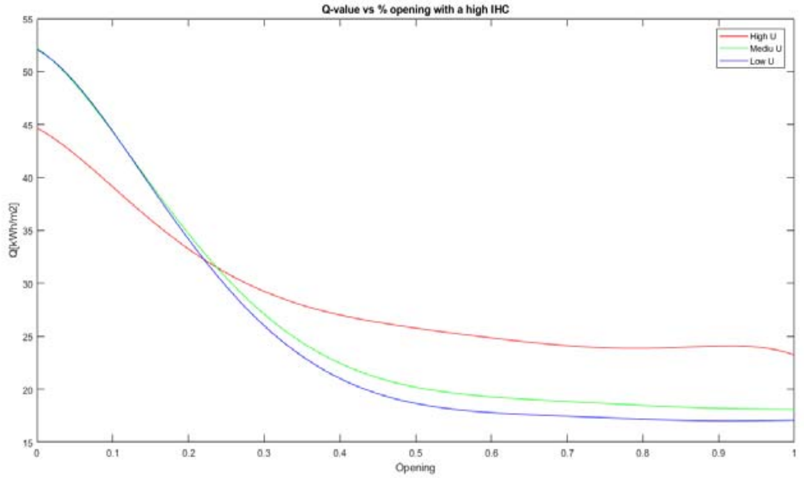

Fig.4. *Q* as a function of windows' opening (case with high *IHC*)

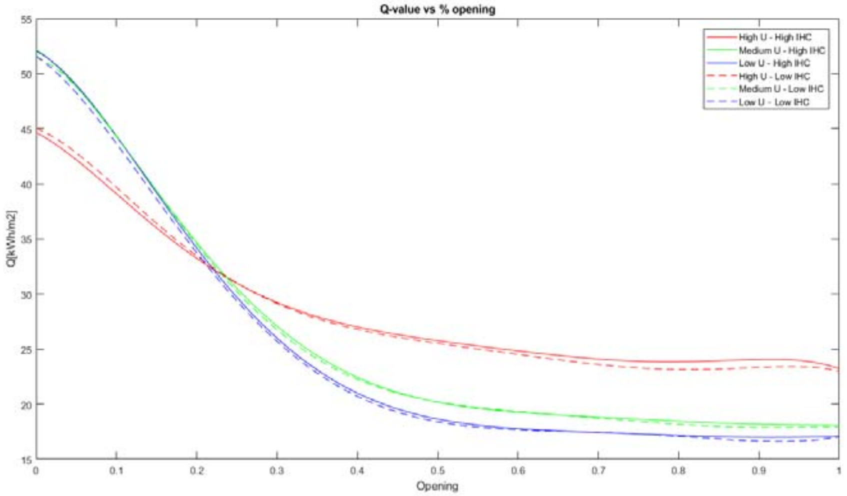

Fig.5. *Q* as a function of windows' openings in all 6 scenarios

As figures 4 and 5 show, the trend of decreasing *Q* with increasing windows' opening percentage, already mentioned in § 3.1, is confirmed up to 60% of opening, above which the added airflow rate does not have a further reduction effect on cooling energy demand.

It is also confirmed that with a low percentage of windows' opening, *Q* decreases with increasing U_{value}, i.e., with decreasing insulation level, for the reasons explained above.

In addition, the graphs of figures 4 and 5 show that this trend has an inversion at 20% of windows' opening in any considered scenario. This means that above 20% of windows' opening, the insulation level starts having an impact synergic with airflow on the reduction of cooling energy needs.

As it was already apparent from tables 4 and 5, the *IHC* is deemed to have an insignificant impact on the cooling energy reduction related to night ventilative cooling, given the indoor-predominant heat generation of the considered office space.

4 MODEL ACCURACY

In linear regression, the function chosen is of great importance. The objective was to find one that could generate small errors, without overfitting or increasing too much the complexity. However, the chosen sixth-degree polynomial function, as any function, approximates the real phenomenon. In addition, the uncertainty in the occupancy increases the discrepancy between data and fitting. The size of the polynomial equation used in modelling cooling energy as a function of opening area was determined by a comparison of the Mean Squared Error (MSE) of testing data for polynomial equations ranging from 1st to 10th degree.

These values are shown table 6.

Table 6. MSE of testing data for different polynomial equations

	Polynomial degree									
Scenarios	***1st***	***2nd***	***3rd***	***4th***	***5th***	***6th***	***7th***	***8th***	***9th***	***10th***
High U-value/Low IHC	10.572	1.26	0.3385	0.3315	0.306	0.2025	**0.1795**	0.184	0.2265	0.244
Medium U-value/Low IHC	26.138	2.5105	0.6015	0.442	0.1975	0.1585	0.159	0.159	**0.1385**	0.147
Low U-value/Low IHC	31.723	2.668	1.433	0.87	0.3635	**0.282**	0.368	0.367	0.349	0.385
High U-value/High IHC	6.503	0.6615	0.344	0.2915	0.2265	0.222	0.221	0.224	0.249	0.29
Medium U-value/High IHC	19.2345	2.1545	0.377	0.3345	0.14	0.1335	0.1355	0.13	0.119	**0.114**
Low U-value/High IHC	37.791	3.499	0.8635	0.4315	0.226	0.202	0.202	0.1975	**0.162**	0.166

The size that minimizes the error, indicated in bold, varies from one scenario to another. However, since the goal was to develop a model that could be applied to all scenarios, the 6th-degree polynomial was chosen as the one generating small errors for all scenarios without overfitting. Overfitting occurred in some cases when a higher polynomial degree was used.

5 CONCLUSIONS

By analysing the above shown results, a conclusion can be made that the amount of energy needed to cool an office space (*Q*) through a CNV technique, in a moderate climate, decreases with increasing the net area of windows' opening. This trend stabilises around 60% of opening, above which no significant effect on the reduction of cooling energy is brought by further increase of opening. The correlation between *Q* and percentage of net opening area can be modelled by a sixth-degree polynomial function with an acceptable accuracy.

It was also found that, up to 20% of windows' opening, increasing the envelope insulation level has a negative effect on the potential reduction of cooling energy need. This trend is reversed above that percentage, when any additional increase in insulation brings a decrease in cooling energy need.

Finally, contrary to what was expected, the internal heat capacity of the building showed not to have any significant effect in the potential cooling energy reduction at any percentage of windows' opening area. However, authors aim at improving this early-research outputs by comparing them with in situ monitoring data.

6 ACKNOWLEDGEMENTS

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