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Natural ventilation for passive cooling by means of optimized control logics

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Abstract

Natural ventilation is one of the most efficient solutions to improve thermal comfort in buildings, particularly for passive and hybrid cooling. This paper analyses the potential of building automation systems for ventilative cooling in residential buildings. In relation to internal and external temperature, an optimized control strategy of window opening is developed to ensure adequate levels of indoor thermal comfort, reducing energy consumption for cooling. In particular, the control of ventilation is calibrated by an optimized variable set-point and a Particle Swarm Optimization (PSO) method is adopted with objective function that minimizes the thermal discomfort hours. The PSO algorithm is implemented in MATLAB and integrated with TRNSYS energy simulation software. A case study focusing on an existing Italian typical building of the '60s, situated in the Mediterranean climatic context is presented. Thermal comfort analysis, according to the adaptive thermal comfort theory (EN 15251-2007), shows that the optimized control logics for natural ventilation determines a significant reduction of overheating discomfort in reference to the case with ventilation only for indoor air quality at fixed hours. Combining the passive cooling system with an active cooling, there are also reductions in energy consumptions for cooling. The results show how the proposed optimized control logics increase the potentialities of natural ventilation strategies to the improvement of energy and thermal performance of buildings, integrating or replacing the conventional efficiency strategies.

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Keywords: Natural ventilation; passive cooling; building automation; particle swarm optimization.

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Nomenclature

BA	Building Automation
BAS	Building Automation Systems
PSO	Particle Swarm Optimization
$T_{optimal}$	Optimal temperature
T_{indoor}	Indoor temperature
$T_{outdoor}$	Outdoor temperature
N_{heat}	Total discomfort hours for overheating
N_{cool}	Total discomfort hours for undercooling
s.f.	Shading factor
IAQ	Indoor Air Quality
HVAC	Heating Ventilation and Air Conditioning
NZEB	Nearly Zero-Energy Buildings
PMV	Predicted Mean Vote
U-value	Coefficient of heat transmission (W/m^2K)

1. Introduction

In the building sector, the energy used for cooling is taking on an increasing share in the energy balance especially in Mediterranean climate, as a result of the increasing use of mechanical conditioning device [1].

The adoption of passive solutions allows a significant reduction of greenhouse gases emissions and addresses the emerging trend of Nearly Zero-Energy Buildings (NZEB), according to the 31/2010 European directive [2]. Passive techniques, such as natural ventilation and solar shading, could satisfy the indoor comfort while minimizing the use of active systems in buildings. Natural ventilation is a low-cost passive solution able to guarantee both Indoor Air Quality (IAQ) and thermal comfort in buildings, by reducing the demand for mechanical ventilation and air conditioning [3]. Specific studies show that application of natural ventilation techniques may decrease the cooling load of buildings and improve indoor comfort and air quality. In particular, Boukhris *et al.* [4] study the natural ventilation as the main passive strategy to reduce overheating in the Tunisian summer climate. Moreover, in [5] four different ventilation strategies with the combination of various building envelope characteristics are simulated for hot-humid climate in Singapore.

On the other hand, in recent years, Building Automation Systems (BASs) associated with control and optimization techniques are widely used to reduce building energy consumption and improve indoor comfort [6], [7]. Many researches deal with the control of active systems, others both on active and passive systems, and only few researches focus on BASs for passive components. For instance, in [8] an intelligent controller is designed to determine the optimal ventilation rate in active systems, by maintaining the indoor CO_2 concentration in the comfort zone and by reducing energy consumption. Moreover, due to the non-linearity of the proposed model, Particle Swarm Optimization (PSO) is adopted to obtain the optimal ventilation rate: the relationship between the ventilation rate and the corresponding power consumption is described by fuzzy logic. Castilla *et al.* [9] propose a multivariable nonlinear model predictive control system to maintain thermal comfort and IAQ by means of Heating Ventilation and Air Conditioning (HVAC) systems and natural ventilation. The main control objective is to maintain users' thermal comfort and IAQ inside a comfort zone defined by the Predicted Mean Vote (PMV) and the IAQ indices, respectively, minimizing, at the same time, the energy consumption necessary to achieve this comfort. In addition, Sun *et al*. [10] propose an integrated control of active and passive heating, cooling, lighting, shading and ventilating system with the aim of minimizing total energy costs. To solve the optimization problem with the coupling HVAC capacity constraints, Lagrangian relaxation is used to obtain a near-optimal solution. In [11] the authors use for the control of the natural ventilation an energy management algorithm implemented in the Energy Plus simulation. In particular, the algorithm consists of the following three components: rules on indoor air quality based on CO_2 sensors, rules on thermal comfort to prevent the overcooling, rules to reduce the risk of air draft.

Concerning the related literature, it is apparent that the contributions focusing on passive systems base the choices on heuristic approaches, while optimization strategies are mainly used for active system operations. Hence, evaluating the effects of passive strategies to reduce energy waste and thermal discomfort by means of optimized BASs is an open problem.

This paper proposes a Building Automation (BA) and optimization strategy for natural ventilation control of passive cooling in residential buildings. Starting from a preliminary work [3] based on a simulation study and what-if analysis, in [12] the thresholds for window opening and closing are optimized. In this paper, we add solar shading to natural ventilation and in this new configuration the control logic is optimized to minimize the thermal discomfort. Moreover, an active cooling system is introduced to assess the effects of the proposed control logics on the energy consumption. The natural ventilation and solar shading effects are analyzed by a co-simulation strategy: TRNSYS and TRNFLOW software simulates thermal building behavior and ventilation dynamics and a PSO algorithm implemented in MATLAB optimizes the thresholds for window opening, by employing the simulation outputs. In particular, the control of ventilation is calibrated on dynamic set-points based on optimal temperatures according to the adaptive thermal comfort theory (EN 15251-2007) [13]. Furthermore, the proposed co-simulation architecture allows assessing the benefits of the proposed optimization strategy. The analyzed case study considering a residential building located in the southern Italy evaluates the improved performances obtained by the optimized control logics in the Mediterranean climate.

The paper is organized as follows. Section 2 describes the natural ventilation control strategy and Section 3 proposes the simulation environment. Finally, Section 4 presents the case study and Section 5 draws the conclusions.

2. Natural ventilation control strategy

The designed energy efficiency solution consists in an on-off control strategy managing the natural ventilation, by opening and closing windows at suitable time intervals.

Now, let denote by $\mathcal{T} \in \mathbb{N}$ a natural number equal to a considered year time period that is divided in actuating time intervals $t = 0,1, \dots, \mathcal{T}$. The control of ventilation is calibrated on the basis of the optimal temperature $T_{optimal}(t)$ for $t = 0,1, \dots, \mathcal{T}$, calculated according to the standard EN 15251 [13], by assuming the category n. II (relative to new construction and existing buildings subject to refurbishment). In particular, the optimal comfort range is $[T_{optimal}(t) - 3°C,\ T_{optimal}(t) + 3°C]$. Moreover, denoting respectively by $T_{indoor}(t)$ and $T_{outdoor}(t)$ for $t = 0,1, \dots, \mathcal{T}$ the indoor and external temperature, the ventilation control logic is applied by defining the following on-off control condition:

windows opened if $T_{indoor}(t) > T_{optimal}(t) + \Delta 1$ *for t=0, 1,…,* $\mathcal{T}$ (1)

and

if $T_{indoor}(t) + \Delta 2 < T_{outdoor}(t) < T_{indoor}(t)$ *for t=0, 1,…,* $\mathcal{T}$ (2)

windows closed otherwise

with

$$\Delta 1 \in \mathbb{R}\ and\ \Delta 1 \in [-6°C, 6°C] \tag{3}$$

$$\Delta 2 \in \mathbb{R}\ and\ \Delta 2 \in [-10°C, 0°C]. \tag{4}$$

Equations (1) and (2) allow the windows opening when the outdoor temperature is favorable to the reduction of overheating thermal discomfort. In addition, in equation (2) Δ2 is introduced to close the windows if the outdoor temperature is too low in comparison with the indoor temperature in order to limit the undercooling discomfort conditions.

The values of Δ1 and Δ2 are determined through the PSO optimization strategy with the aim of minimizing the thermal discomfort, i.e., the total discomfort hours $N(\Delta 1, \Delta 2)$ for overheating (N_{heat}) and undercooling (N_{cool}):

$$F_{obj} = min_{\Delta 1,\Delta 2} N(\Delta 1, \Delta 2) = min_{\Delta 1,\Delta 2}[N_{heat}(\Delta 1, \Delta 2) + N_{cool}(\Delta 1, \Delta 2)] \quad (5)$$

subject to (3) and (4).

The numbers of discomfort hours for overheating and undercooling are determined according to the adaptive thermal comfort theory EN 15251 as follows:

- N_{cool} is the number of hours in which $T_{indoor}(t) < T_{optimal}(t) - 3°C$
- N_{heat} is the number of hours in which $T_{indoor}(t) > T_{optimal}(t) + 3°C$.

In order to evaluate the impact of the solar shading in the proposed BA strategy, rolling window shutters are introduced and ruled on the basis of the *shading factor* (s.f.) that represents the percentage of opaque area due to the shading respect to the glazing surface of the window. Moreover, two operative conditions that consider the presence or absence of users are studied:

- s.f. = 0.25 (presence of users)
- s.f. = 0.75 (absence of users).

This assumption simulates users, careful about the problems of thermal and visual comfort, who close rolling window shutters by obtaining a shading percentage of the windows equal to 75 % (s.f.= 0.75) in unoccupied rooms, and a shading percentage equal to 25 % (s.f.= 0.25) to avoid dark rooms when users are present. Then, the airflow opening areas are modified according to the specified percentages.

3. Simulation environment

In this section the co-simulation architecture is presented to integrate the optimization algorithm with the building behavior simulation and the air flow network model. More details about this architecture can be found in [12].

3.1. Energy simulations

The building thermal behavior is modeled by TRNSYS v.17 software [14], a complete and extensible simulation environment for the transient simulation of systems, including multi-zone buildings. One of the key factors in TRNSYS is its modular and flexible architecture based on Dynamic-Link Library (DLL) concept, which facilitates the addition to the program of new component models, not included in the standard TRNSYS library.

Moreover, in this study the thermal building module (Type 56) is integrated by TRNFLOW software that models the air flows between outdoor and indoor air nodes. In particular, this multizone airflow model schematizes the building as a network of nodes and airflow links. The nodes represent the rooms and the building surrounding and the links depict openings, doors, cracks, window joints and shafts, as well as ventilation components like air inlets, outlets, ducts and fans. The boundary conditions are the wind pressures on the façade and the indoor and outdoor air temperatures.

3.2. Particle Swarm Optimization

This subsection specifies the application of the PSO algorithm [15], a stochastic metaheuristic optimization algorithm. The rationality of choosing the PSO algorithm with respect to other evolutionary methods is that the PSO is robust, efficient, suitable to handle non-linear problems and requires fewer number of function evaluations than genetic algorithms, while leading to better or the same quality of results [15].

In the PSO a number of simple entities, called particles, is used for optimization purposes: the particles represent candidate solutions with respect to the problem being optimized. In particular, each particle of the swarm is composed of three D-dimensional vectors, where D is the dimension of the search space: the current position x_i, the previous its best position p_i, and the velocity p_i. The particles are placed in the search space of some problem or function, and each of them evaluates the objective function at its current location. In detail, the current position x_i can be considered as a set of coordinates describing a point in the space and is evaluated as a possible problem solution. If such position results to be better than the previous ones, then its coordinates are stored in the vector p_i. The value of the resulted best function is stored in a variable called previous best $pbest_i$, for comparison on the later iterations. The objective of each particle is to find better positions and update p_i and $pbest_i$ vectors. For this reason, the algorithm iteratively updates the velocity vector v_i of each particle and calculates new positions x_i, also considering the best location of all particles (*gbest*), in accordance with the following two-update equations:

$$v_i(k+1) = w \cdot v_i(k) + c_1 \cdot r_1^{(k)} \cdot [pbest_i(k) - x_i(k)] + \ldots + c_2 \cdot r_2^{(k)} \cdot [gbest(k) - x_i(k)] \quad (6)$$

$$x_i(k+1) = x_i(k) + v_i(k+1) \quad (7)$$

where w is the inertia weight, k is the iteration number, c_1 and c_2 are respectively the cognitive and social weight, r_1 and r_2 are vectors of random numbers sampled from a uniform distribution in the range [0,1].

Since the aim is minimizing the objective function $N(\Delta 1, \Delta 2)$, the current position $x_i(k) = [\Delta 1(k)\ \Delta 2(k)]^T$ is the vector of the values that Δ1 and Δ2 assume at iteration k. In addition, the parameters w, c_1, c_2 and the particle numbers have to be appropriately chosen, depending on the problem to be solved: in the case study we fix $w = 0.7298$, $c_1 = c_2 = 1.49618$ and set the size of the population equal to 10 particles [16].

Finally, the optimization process is completed if the best location $gbest$ does not change for a fixed number M of consecutive iterations. The corresponding value $F_{obj} = N(gbest)$ is the optimal value of the objective function determined by the PSO.

3.3. Co-simulation architecture

The co-simulation architecture including TRNSYS and MATLAB is obtained using MATLAB as the main software that calls TRNSYS for the iterations. The proposed architecture is shown in Fig.1 that points out the inputs and data exchanged among the simulation software and the optimization algorithm.

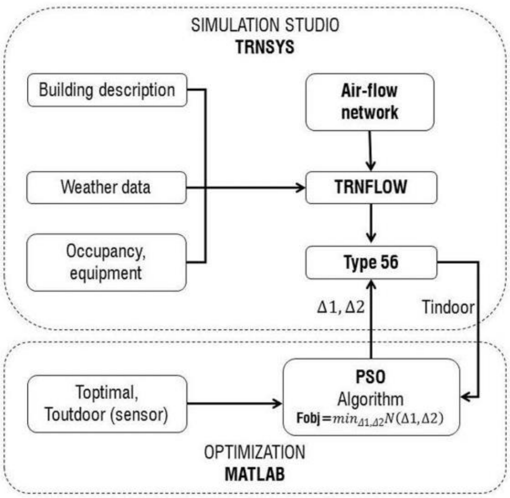

Fig. 1. Co-simulation architecture integrating TRNSYS and PSO algorithm.

More precisely, the MATLAB program implementing the PSO algorithm receives the data about the indoor temperature ($T_{indoor}(t)$) from TRNSYS and determines the value of the objective function (5) considering the temperatures $T_{optimal}(t)$ and the outdoor temperature ($T_{outdoor}$). Then, the MATLAB program computes new values of Δ1 and Δ2 on the basis of the determined objective function. The Δ1 and Δ2 values are transmitted to TRNSYS that implements the control strategy (1) and (2) to command the window opening. Iteratively, the PSO algorithm updates the values of the two decision variables Δ1 and Δ2 in order to minimize $N(\Delta 1, \Delta 2)$, storing the best couple of decision variables Δ1 and Δ2. When the iteration process is terminated, the PSO algorithm returns the optimal values Δ1 and Δ2 that minimize (5).

4. Case Study

4.1. Building description

The case study considers a residential building typical of the '60s years, located in the urban context of Bari (Italy, 41° 07'31 "N 16 ° 52'00" E, 5 m.a.s.l.). The dwelling is situated at an intermediate floor and has a net floor area of about 100 m^2, with windowed sides faced to northwest and southeast. The plant of the dwelling is shown in Fig. 2.

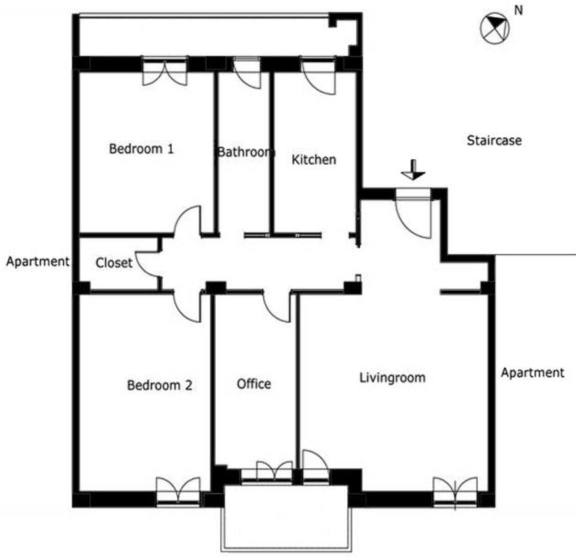

Fig. 2. Dwelling plant.

The building envelope parameters are typical for the Italian residential buildings of '60s and are reported in Table 1.

Table 1. Thermal characteristics of building envelope.

Items	U- value (W/m^{2}K)
External wall	1.10
Staircase-dwelling wall	1.54
Floor	0.83
Windows	5.6

In reference to this specific case study, the energy hourly variations for occupancy, lighting and domestic appliances are implemented using typical fixed schedules. As regarding the solar shielding systems, rolling window shutters are adopted with a scheduled operation in function of users presence as described in Section 2. The Table 2 shows the scheduled daily occupancy of each room.

Table 2. Scheduled daily occupancy for each room.

Room	Occupancy daily time slots
Bedroom2	From 6 p.m. to 8 a.m.
Kitchen	From 7 a.m. to 9 a.m.; from 12 p.m. to 2 p.m.; from 8 p.m. to 10 p.m.
Bedroom1	From 10 p.m. to 8 a.m.
Office	From 9 a.m. to 12 p.m.; from 3 p.m. to 7 p.m.
Living room	From 8 a.m. to 9 a.m.; from 4 p.m. to 12 a.m.

The type of windows is tilt-turn window, with automated bottom-hinged opening (corresponding to the 50% of the opening for windows with two shutters). The detailed description of air permeability characteristic of building envelope is reported in [3].

4.2. Simulated cases and results

The adaptive thermal comfort simulations and results refer to Bedroom2 that is resulted the most uncomfortable room according to the adaptive thermal comfort without active cooling system. Then, the indoor temperature T_{indoor} of Bedroom2 is considered to control the openings of all the dwelling windows. The considered period for the simulations is July-August hence the simulation runs are of $\mathcal{T}$ =1488 hours with hourly time step *t*. The simulation results take into account only the hours with users presence in Bedroom2 (see Table 2) for a total of $\mathcal{T}_o$= 868 hours.

The simulations are executed considering three cases:

- Case 0: natural ventilation only for IAQ at fixed hours;
- Case 1: ventilative cooling under control rules (1) and (2) with Δ1= 0°C, Δ2= -3°C;
- Case 2: ventilative cooling under control rules (1) and (2) with optimal values of Δ1 and Δ2.

More precisely, in Case 0 the windows are opened only at certain hours (8 a.m. - 10 a.m.; 1 p.m.- 2 p.m.; 8 p.m. - 9 p.m.) during the activities of preparing and cooking foods and of household cleaning.

Moreover, in Case 1, in addition to the natural ventilation for IAQ of the Case 0, during the other daily hours ventilative cooling is granted under control rules (1) and (2), where the values of Δ1 and Δ2, as previously specified, are fixed a priori on the basis of the what-if analysis results obtained in [3].

Furthermore, Case 2 uses the optimal values obtained by the proposed co-simulation and optimization strategy: the optimal objective function values are obtained with Δ1= -1.07 °C and Δ2= -7.51°C corresponding to the 16th PSO iteration (as it is highlighted in Figs. 3 and 4). In particular, Fig.3 shows the optimization running: the iterative optimization procedure starts assigning random values to Δ1 and Δ2 subject to (3) and (4). According to the values of Δ1 and Δ2, the set-point temperature for the window opening activation in (1) and (2) varies. In Fig. 4 it is possible to notice how the discomfort conditions vary from a maximum of about 700 hours to a minimum of about 80 hours. Furthermore, Figs. 3 and 4 highlight how function $N(\Delta 1, \Delta 2)$ is more sensitive to the variations of Δ2 with respect to the variations of Δ1. This result is due to the effects of Δ2 in (2): increasing the absolute value of Δ2 allows ventilation also in the case of lower outdoor temperatures and consequently it enhances passive cooling.

The results of the simulations are compared by computing the following performance indices:

- N_{heat}, number of discomfort hours for overheating in $\mathcal{T}_o$
- N_{cool} , number of discomfort hours for undercooling in $\mathcal{T}_o$
- N , total number of discomfort hours in $\mathcal{T}_o$
- $N_{heat}/\mathcal{T}_o \cdot 100$, percentage of discomfort hours for overheating
- $N_{cool}/\mathcal{T}_o \cdot 100$, percentage of discomfort hours for undercooling

- N / $\mathcal{T}_o$·100, percentage of discomfort hours.

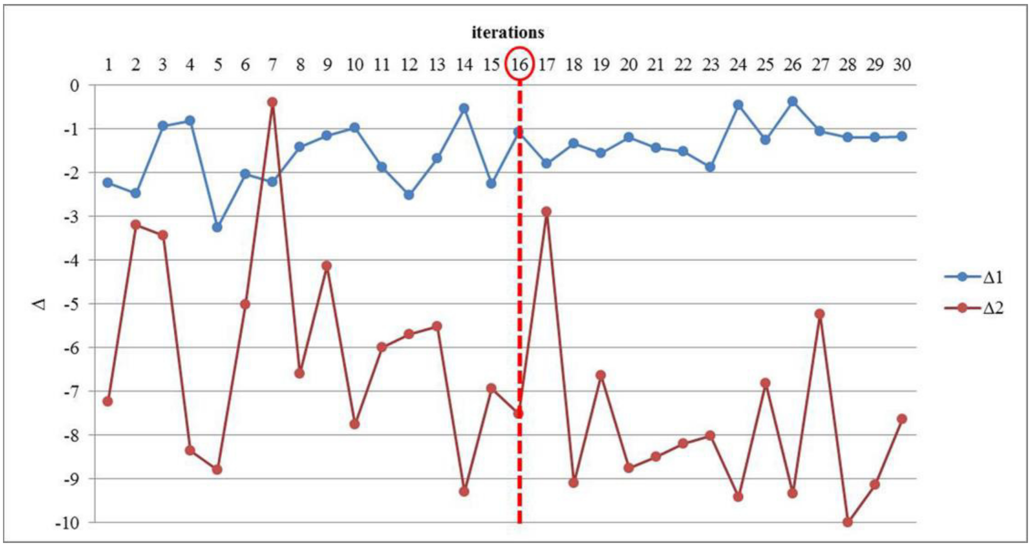

Fig. 3. The optimization running.

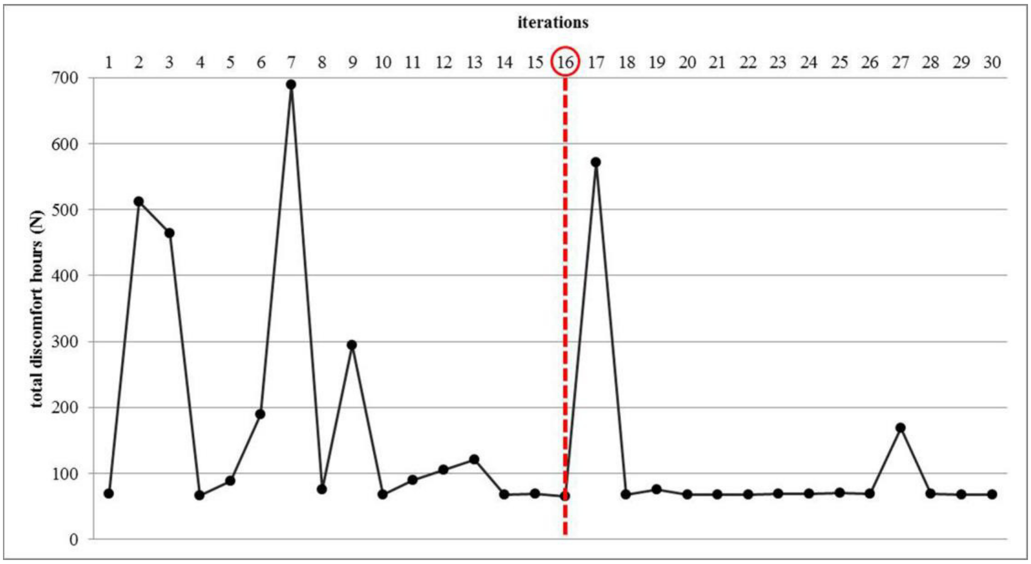

Fig. 4. The total number N of discomfort hours in function of Δ1 and Δ2.

The computed performance indices are reported in Table 3. Comparing Case 1 and Case 2 with respect to Case 0, Fig. 5 and Table 3 show that the natural ventilation control logics allow significant reductions of the total thermal discomfort hours. The total thermal discomfort percentage moves from 32.9 % (Case 0) to 13.3 % (Case 1) and to 8.7 % (Case 2). In particular the reduction of total discomfort hours depends from the overheating discomfort conditions that decreases about 65 % in Case 1 and about 81 % in Case 2 with respect to Case 0. On the other hand, the natural ventilation control logics do not determine variations of thermal discomfort for undercooling.

Table 3. Results about thermal comfort and energy needs for cooling.

Case	Thermal discomfort (no active system)						Energy needs for cooling (with active system)	
	Overheating		Undercooling		Total			
	N_{heat}	%	N_{cool}	%	N	%	E (kWh)	Δ%
Case 0	262	30.2	24	2.7	286	32.9	178	-
Case 1	91	10.4	25	2.8	116	13.3	134	-24.5
Case 2	49	5.6	27	3.1	76	8.7	121	-32.1

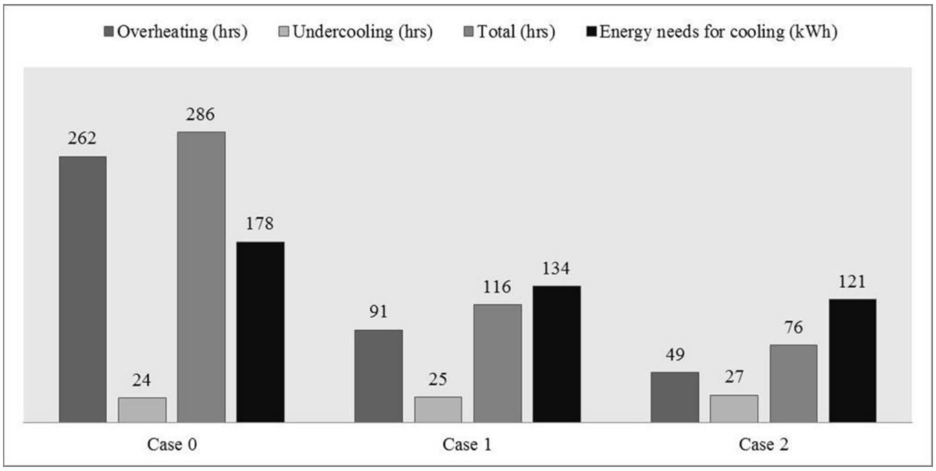

Fig. 5. Adaptive thermal comfort and energy results.

In order to value the effectiveness of window opening control logic on the energy consumptions, the three cases previously examined are performed by adding an active cooling system. The cooling system is switched-on in each room when $T_{indoor}(t)$>26° according to the scheduled occupancy shown in Table 2. Hence, the energy E needed for cooling referred to Bedroom2 is reported in Table 3 and Fig. 5 for the three cases. The results show how the proposed passive strategy for window opening allows reducing of the energy needs, that in Case 1 are reduced of 24.5% and in Case 2 of 32.1 % respect to Case 0.

5. Conclusions

This paper proposes a Building Automation (BA) strategy for the ventilation control of passive cooling in residential buildings situated in the Mediterranean climatic context. In particular, the objective of the paper is to determine a natural ventilation control strategy on the basis of the following issues: i) the thermal comfort analysis according to the adaptive thermal comfort theory (EN 15251-2007); ii) the optimal values of the thresholds for the on-off control rule to reduce the overheating discomfort also in presence of solar shading. To this aim, the paper proposes a co-simulation approach that uses TRNSYS and TRNFLOW for simulating the thermal building behaviour and a PSO algorithm implemented in MATLAB to determine the optimal temperature set point for window opening.

A case study simulation, considering a residential building located in the southern Italy, shows the benefits of the natural ventilation strategy applied by the optimized control logic. In particular, the thermal comfort and energy analysis show the improvement of dwelling thermal performances with significant reduction of overheating discomfort hours and reductions of energy needs for cooling.

Future developments will concern the study of window openings control optimized for the whole dwelling, and combined with solar shading activation logics. Moreover, further research will focus on the ventilation control logic applied to hybrid systems also to minimize the energy consumption.

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