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Indoor Air Temperature Control in Buildings via an Optimal Tuned PI Strategy

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***Abstract*— In this paper an optimal PI tuning strategy for the air temperature control embedded in a novel dynamic simulation code for the building energy performance analysis is presented. Precisely, the proportional and the integral gain of the controller are those that minimize a quadratic function of the temperature tracking error and the thermal sensible load. A numerical scheme for solving the resulting optimization problem is also presented. This code, written in MatLab, represents the kernel of an upgraded version of a building simulator proposed in the literature, called DETECt, in which several additional improvements have been also implemented. In order to assess the effectiveness of the proposed PI tuning method and the result temperature control, different case studies related to three reference buildings, with different geometries and envelope constructions, located in several European weather zones are considered.**

Index Terms—**Indoor air temperature control, advanced building modelling, optimization of PI parameters, closed-loop control systems.**

I. INTRODUCTION

During the last decades, more than half of the total energy consumptions has been primarily due to space cooling and heating energy use [1]. Concurrently, the requests of low energy consumptions and sustainable plans call for attention to reducing energy demands while meeting the increasingly high thermal comfort levels required in buildings [2, 3]. In order to solve such multivariate and challenging problem, researchers focus on the use of energy-efficient control strategies to be used during building design, construction and use [4]. To this aim, building energy simulation models or tools play a crucial role for the prediction of both building energy demand and comfort indexes. The design of accurate building energy forecasting models, with the aim to reduce the outstanding gap between predicted and actual energy consumption, is still an open problem [5]. The development of high-fidelity energy prediction tools or complex mathematical thermal models involves both modelling and analytical skills, due to the nonlinearity of the building energy systems [6]. A thermal model can be provided according to three different modelling paradigms: white box (physics-based); black-box (data-driven); and grey-box (combination of physics based and data-driven) [6]. Among them, grey box models are widely adopted for modelling the thermal dynamics of buildings, since they combine the knowledge of the building physical structure with various data-driven inputs. Although they can be accurate in the estimation of the state of the system (e.g. indoor air temperature), their applicability is limited by the necessity of some a priori knowledge of the thermal dynamics [7]. In order to overcome the above mentioned lacks and limits, a large number of studies now focus on the trade-off between the model accuracy and its simplification [6]. Furthermore simulation model and tools have to be suitable to embed different control structure in order to evaluate the energy performance of future buildings [8]. Such studies remark the need of thermal models in which the on-line control and the optimization of system state, can be suitably performed. Hence, the regulation of building thermal variables, e.g. indoor air temperature, can be achieved by combining the control system and the induced thermal dynamics [7]. From this point of view, building automation and control systems play a remarkable role in order to achieve building energy efficiency and thermal comfort [6, 8]. In this regard, the feasibility of control schemes based on different techniques and their effectiveness for improving the accuracy of building energy performance simulation models have been recently analyzed [8]. Nevertheless, such techniques can provide different results depending on the accuracy and robustness of the adopted control solutions and building simulation approaches [3, 8]. With respect to control it is worth to be noted here that, although in the technical literature advanced control solutions have been recently proposed (see for example those based on model predictive control schemes [9] or artificial intelligence tools, such as, for example, learning methods [8]), fixed gains control algorithms, such as PI and PID controllers, are still widely used. These methods have the great advantage of being easy to be designed and to be implemented [10], but they require the appropriate tuning of control gains to be effective. Automatic and well assessed methods for the tuning of PI/PID control parameters are today available in order to reduce the time required by the tuning phase [11]. Nevertheless, often these methods do not provide any optimality of the solution, which is essential in the context of indoor air temperature control. To overcome this limit, in this paper we propose a novel procedure for the optimal and automatic tuning of the PI gains. The approach is based on a purposely designed cost function to be minimized so to optimize the control gains over a finite control horizon. The adopted cost function weights both the temperature tracking error and the sensible thermal energy required to impose the demanded temperature profile. Due to the complexity of the

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building model, the resulting parameter optimization problem cannot be solved analytically. Hence, an iterative numerical procedure for its solution is also presented in the paper. The optimized control algorithm has been embedded in a new version of a dynamic energy performance simulation code, called DETECt 2.1, which is able to analyse the building thermal behaviour and to assess the benefits of different and advanced building envelope techniques, solar gain controls and daylighting solutions in case of different weather locations, envelope materials, building shapes, orientations and geometries. In addition, temperatures dynamic profiles and time-variant spatial trends can be obtained. We note that, in the first release of DETECt, presented in [12], the PI gains were online selected by using an heuristic scheduling method [13]. The paper is outlined as follows. In Sec. II the building model implemented in the DETECt code and used for the optimization procedure is presented. In Sec. III the optimal tuning strategy for PI gains is given with a numerical scheme for solving iteratively the optimization problem, while in Sec. IV several case studies for the test of the overall system are presented before discussing the simulation result in Sec. V.

II. A DETAILED BUILDING MODEL

The first step to be carried out in a detailed building energy simulation analysis is the assessment of building heating and cooling loads and demands. In particular, for each building thermal zone, the calculation procedure starts from the analysis of the related heat flows, which depend on: i) heat conduction transfer through the envelope, ii) indoor and outdoor convection and radiation, iii) sun radiation transmission through fenestration, iv) heat gains due to building equipment and occupants, v) ventilation and air infiltration. In the presented code, the transient heat transfer through the building envelope is based on the one-dimensional heat flow assumption [14]. Among the available techniques based on lumping the distributed capacitance and resistance of a material layer together at nodes, the thermal network method is widely used as alternative to the simple energy balance assessment [15]. Although very simple thermal network models consist of system thermal masses lumped in a single node, real building elements are often composed by different structural and energy saving insulation materials in mutual thermal contact [16]. In these cases, being the allocation of heat capacities and thermal resistances a complex function of the space, thermal models obtained by distributed parameters are always preferred [17]. By following such approach, in DETECt the thermal behaviour of each multi-layer building element is modelled by a thermal RC network. Here, thermal masses and conductivities are uniformly discretised into a suitable number, N, of thin sub-layers of different thicknesses. The indoor air of a thermal zone is modelled as a single indoor air temperature node, while the construction envelope is subdivided into M multi-layer building elements (wall, floor, roof, horizontal and vertical internal partition and window).

In Fig. 1 a scheme of the N +2 nodes thermal network related to the generic m-th building element is depicted. Here, The energy flow paths include the heat conduction through building elements and the most important occurring phenomena, such as solar heat gains through windows, infrared heat exchanges, internal gains and ventilation.

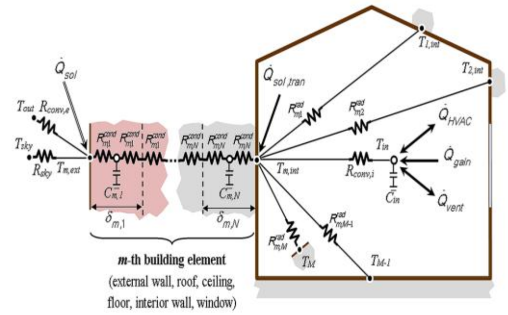

Fig. 1: Sketch of the thermal RC network.

In each τ-th time step and for each j-th capacitive node, $j = 0, \ldots, N$, of the m-th building element $m = 0, \ldots, M$, the differential equation describing the energy rate of change of each temperature node of the building envelope is

$$C_{m,n}\frac{dT_{m,n}}{dt}=\sum_{j=n-1}^{n+1}\frac{T_{m,j}-T_{m,n}}{R^{eq}_{m,j-1}}+\dot{Q}_{m,n} \tag{1}$$

The differential equation on the thermal network node, *in*, of the indoor air that has to be solved simultaneously with the system of eq. (1), is

$$C_{in}\frac{dT_{in}}{dt}=\sum_{m=1}^{M}\frac{T_{m,N}-T_{in}}{R^{conv}_{m,int}}+\dot{Q}_g+\frac{(T_{out}-T_{in})}{R_v}\pm\dot{Q}_{AC} \tag{2}$$

Here C, T and R are thermal network capacitances, temperatures and resistances, respectively. $R^{eq}_{m,j\text{-}n}$ is the sum of the halves sub-layers thermal resistances that link each node to their neighbours. $R^{conv}_{m,int}$ is the convective thermal resistance calculated as a function of the surfaces condition (vertical or horizontal wall; ascendant or descendant flow). R_v describes the air ventilation and infiltration thermal load and links the indoor air node to the one related to the outdoor air, whose temperature is T_{out}. $\dot{Q}_{m,n}$ Represents the generic thermal source term only acting on non-capacitive nodes and it takes into account the solar and long wave radiation contribution. Notice that in case of non-capacitive nodes related to the interior and exterior surfaces, the algebraic equation that describes the related heat transfer is obtained by eq. (1), by setting $C_{m,n}$ to zero. A whole building is modelled through a thermal network of M x N nodes, whose set of differential and algebraic equations is obtained by (1) and (2). A detailed description of the developed model for the dynamic building energy performance simulation is reported in [12]. The above described building model has been implemented in DETECt which is composed by different

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calculation modules depicted for sake of completeness in Fig. 2.

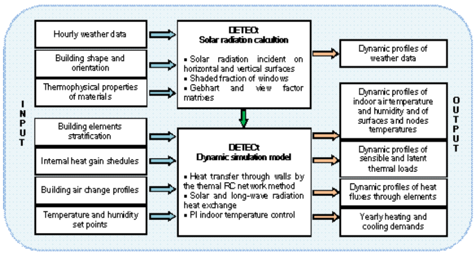

Fig. 2: Schematization of the DETECt simulation modules.

In this paper we focus on improving the PI strategy by selecting as PI gains those obtained as optimal according to a cost function. The tuning method is described in Sec. 0 while Further details on DETECt simulation code can be found in [12].

III. OPTIMAL TUNING OF PI CONTROL PARAMETERS

Given the tuple (A,B,C), with $A \in R^{n\times n}$, $B \in R^n$ and $C \in R^{1\times n}$ we define the following system:

$$\begin{cases} \dot{x} = Ax + Bu + F(x,t) \\ y = Cx \end{cases} \tag{3}$$

Where $x \in R^n$ is the state vector, $u, y \in R$ are the system input and output, respectively, and $F(x,t) \in R^n$ is a vector function embedding all the time varying and nonlinear terms acting on the system dynamics. In what follows we assume system (3) to be controlled via a PI algorithm, hence:

$$u(t) = K_p e(t) + K_I \int_{t_0}^{t} e(\tau)d\tau, \tag{4}$$

where $e(t) = r(t) - y(t)$ is the tracking error between the system output *y(t)* and a prefixed time-varying reference trajectory $r(t)$; K_P and K_I are control gains to be opportunely tuned; t_0 is the initial time instant. As usual, closed-loop dynamics strongly depend on the specific choice of the control gains. Indeed a wrong selection of these parameters may jeopardize the system performance, leading to instability in some critical cases. Moreover, the tuning procedures, based on heuristic methods, may result to be time-consuming or not effective. To solve this problem, different experimental or model based methodologies have been proposed in the control literature for the appropriate gains tuning with the aim of guaranteeing stability and robustness (see for example [11], [18] and references therein for a complete overview of standard and innovative PI tuning procedures). Here we propose a different approach based on a purposely designed cost function to be minimized so to optimize the control gains. Specifically, consider a positive function, say $J(K_P, K_I)$, so that:

- $J(K_P, K_I)$ assumes finite values for stable solutions of system (3) under the control action (4);
- smaller values of $J(K_P, K_I)$ corresponds somehow to a better tracking of the reference trajectory;

The control gains are set as $K_P = K_P^*$ and $K_I = K_I^*$ so that

$$J\left(K_P^*, K_I^*\right) = \min_{(K_p, K_I)} \left\{ J\left(K_p, K_I\right) \right\}. \tag{5}$$

According to this approach, different choices of $J(K_P, K_I)$ can be made in order to derive the PI gains according to (5). In this paper, we consider the following quadratic function measuring both mean squared tracking error and control effort over a finite control horizon as:

$$J\left(K_p, K_I\right) = \int_{t_0}^{t_0+T} \left[qe^2(\tau; K_p, K_I) + hu^2(\tau; K_p, K_I) \right] d\tau, \tag{6}$$

being q and h positive constants that weigh the terms in integral (6), and T the finite time interval that is of interest in the control problem (control horizon). Notice that the optimization problem discussed here is different from the one usually considered in optimal control theory where the controller structure is not a priori fixed. Here instead the structure of the controller is fixed to the PI structure (4) and the aim is the parameters optimization. Moreover, differently from the classical linear quadratic optimal control, here numerical methods are exploited to solve the parameter optimization problem in (5) that cannot be solved in closed form due to its complexity. The iterative procedure proposed to numerically solve the optimization problem is shown in Fig. 3. This procedure is implemented by the following tools: *(i)* an optimization toolbox *(Optimizer),* which decides the parameters $(K_P^{(i)}, K_I^{(i)})$ for the *i-th* interaction; *(ii)* a detailed simulator of the controlled system i.e the plant (3) under the control action (4). (Note that the *Simulation-Code* block in Fig. 3 provides the data necessary to compute the function J); *(iii)* the *Compute-J* subsystem allows the computation of the J-function at each interaction.

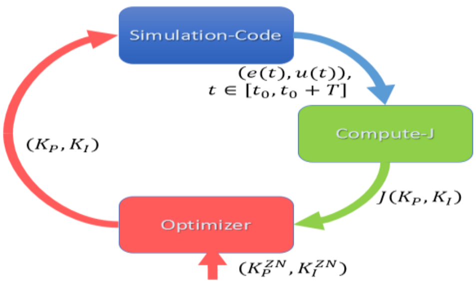

Fig. 3: Iterative procedure adopted to numerically solve the optimization problem (5).

We remark that, as the optimization problem is numerically solved by an iterative procedure, the initial condition plays a fundamental role for the rate of convergence [19]. Moreover, initial conditions have to guarantee the stability of the

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controlled system at the very first interaction. Note that the stability at the generic *i*-th interaction (*i >1)*, is instead ensured by the Optimizer itself, since unstable solutions lead to high values of J (6), and therefore they are automatically excluded. For these reasons, the optimization procedure is initialized by using by selecting the PI gains with the closed-loop Ziegler and Nichols method [11] (denoted as K_P^{ZN}, K_I^{ZN} in Fig. 3). Furthermore, optimization toolboxes are available in most of the numerical software packages (as, for example, MatLab, Maples, etc.), so the minimization problem of the equation (5) can be effectively solved. Note that, the proposed approach can be extended to the generic problem of tuning feedback control actions parameters described as:

$$\begin{cases} \dot{x}_c = f\left(x_c, e; \xi\right) \\ u = g\left(x_c, e; \xi\right) \end{cases} \quad (7)$$

Where: x_c is the state of the controller; f and g are liner or nonlinear functions for mapping the tracking error and the state of the controller onto the state derivative and control action; while ξ is the set of the control parameters to be selected. In this case the cost function J must be a positive function of the parameter vector ξ.

IV. CASE STUDIES

In order to show the effectiveness of the proposed tuning method to design PI controllers for an accurate tracking of a given indoor air temperature trajectory, which in turns allows a more accurate prediction of the heating and cooling demands in buildings, different case studies have been implemented and analysed by using the new DETECt version. More in detail, we have considered buildings of different geometry, construction materials and subjected to different weather conditions (external disturbances). In the following subsections we describe the typologies of buildings implemented in the simulation code in accordance with model presented in Sec. 0 as well as the design of the optimized PI scheme in Sec. 0 for taming indoor air temperature dynamics.

A. Description of buildings

In the developed case studies different buildig size, construction material as well as outdoor weather conditions are taken into account.

In particular:

- We characterize the building geometry by its square meters floor area. Thus, a small size dwelling (Fig. 4a, 48 m^2), a middle size office (Fig. 4b, 200 m^2) and a large size mall (Fig. 4c, 900 m^2) are modelled. Some details about geometry and operating features are reported in Table 1;
- Both light and heavy building envelopes have been considered. Table 2 shows the envelope stratification data for both the simulated buildings;
- Input weather data (such as outdoor temperature, solar radiation, etc.) vary according to hourly profiles and are related to cold winter climates and temperate Mediterranean ones. Details on heating and cooling degree days, HDDs and CDDs respectively, of the investigated weather zones are reported in Table 3. Here, the annual Incident Solar Radiation (ISR) on the horizontal surface of each weather zones are also reported. Note that Meteonorm and TMY3 weather data files are processed.

Hence, 48 case studies have been simulated and analysed, covering a wide range of operating conditions. Furthermore, we assume that the HVAC system of these buildings are intermittently operated [20], i.e. the temperature is not controlled all day long, but only in a given range of hours, defined as occupied hours. Here we assume that the temperature must be constant to a given set-point from 08:00 to 18:00. In particular, the reference set-point is set at 20°C from the October 1st to April 30th and at 25°C from May 1st to September 30th. In addition, for each investigated case study the simulation horizon was set at one year to cover both winter and summer weather conditions (simulation starts on January 1st and ends on December 31st). Additional details on parameters are given in [12].

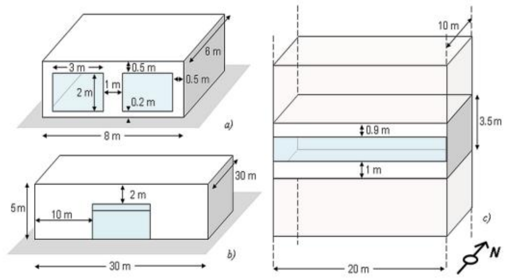

Fig. 4: Small (a), middle (b) and large (c) size buildings.

Table 1: Geometry features of the considered buildings.

	Building		
	Small	**Middle**	**Large**
Surface to Volume ratio (%)	1.3	0.53	0.30
Window to Wall ratio (%)	55	45	20
Air change (vol/h)	0.5	1.0	2.0
People vapour mass flow rate (g/h ·p)	40	45	60

Table 2: Envelope stratification (from inside to outside).

Building element	**Lightweight building**		**Heavyweight building**	
	Materials	**(mm)**	**Materials**	**(mm)**
wall	Plasterboard	12	Concrete block	100
	Fiberglass quilt	66	Foam insulation	61.5
	Wood siding	9.0	Wood siding	9.0
roof	Plasterboard	10	Identical to Lightweight case	
	Fiberglass quilt	111.8		
	Roof deck	19		
floor	Timber flooring	25	Concrete slab	80
	Insulation	1.003	Insulation	1.007

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window	Glass	4.0	Identical to Lightweight case
	Air	6.0	
	Glass	4.0	

Table 3: Climatic zones, HDD and CDD indexes and ISR.

Location	HDD (Kd)	CDD (Kd)	ISR (kWh/m^{2}y)
Copenhagen	3757	77	988
Freiburg	2966	287	1470
Denver	2667	977	1662
Milan	2584	487	1114
Nice	1506	471	1562
Rome	1370	777	1430
Naples	1335	833	1825
Athens	1082	1284	1407

B. Design of the optimal PI algorithm for controlling indoor air temperature

In order to impose the required indoor air temperature set point over the daily interval of interest (from 08:00 to 18:00), a PI controller is adopted. The controller is tuned according to Sec. 0, by taking into account the following design options:

- for the optimization procedure presented in Sec. 0, we select as controlled variable, $y = T_{in}$, the indoor air temperature, and as control input, $u = \dot{Q}_{AC}$, the sensible load of equation (2);
- due to the rather slow dynamics of the building, the controller must be activated in advance with respect to the beginning of the occupied time slot [20]. In particular, the controller is activated at 07:00 each day;
- a smooth transition from the air temperature obtained at 07:00 to the demanded set-point required at 08:00 is imposed. This transition is guaranteed by choosing as reference input to the control system, $r(t)$, the output of an asymptotically stable second order Linear-Time-Invariant (LTI) system. This is built by assuming: *(i)* a settling time of one hour; *(ii)* absence of overshoots in the step response; *(iii)* the demanded steady-state temperature for the occupied time as input. Notice that in order to avoid discontinuities in the system dynamics, the output of the second order LTI system is initialized to the indoor air temperature at 07:00;
- For the cost function of equation (6) we select $q = 100$ and $h = 0.1$. This impose to the optimization procedure to search for the PI gains that allow the resulting indoor air temperature to closely match the reference trajectory;
- in order to reduce the computational time required for finding the optimal PI gains, the optimization horizon, T of equation (6), is set to one day (the first day of the year). Nevertheless, the procedure can also be applied to different days, random or not consecutive.

The numerical architecture depicted in Fig. 3 adopted for solving the optimization problem of equation (5) was implemented in MatLab. In particular as *Simulation-Code*, the DETECt code, based on the thermal model of the building briefly described in Sec. 0, was adopted. The Optimizer block was implemented by using functions of the MatLab optimization toolbox [21]. It must be noted that by adopting a workstation with an INTEL I7 microprocessor and 32 Gb RAM, for the entire set of case studies, the optimization of the PI gains took about one hour. The number of interactions required for solving the problem of equation (5) varied from 5, for the middle-size heavy building located in Denver, to 81, for the small-size light building located in Naples.

V. RESULTS AND DISCUSSION

We first consider the tracking performance achieved by the simulation code when the tuning strategy described in Sec. III is adopted for PI gains. In the following we analyse the time histories for the cases of heavyweight envelope buildings in a cold winter weather zone (Denver) and in a temperate climate one (Naples). For all the presented figures, the meaning of the different adopted colour lines is summarized in Table 4.

Table 4: Colour lines related to each case study.

Location	Buildings		
	Small-size	**Middle-size**	**Large-size**
Denver	blue	green	red
Naples	cyan	magenta	yellow

Even though the simulation time has set to one year (365 days, 8760 hours), we show in Figure 5 the performance of the closed-loop system only for a set of four sample days. Note that such time interval includes the change of the indoor set-point temperature (from 20 to 25°C). Here, it is clearly shown that adopting the control strategy presented in Sec. 0, the indoor air temperature is always controlled at the required temperature set-point (independently of the occurring: initial air temperature; building thermal inertia; weather conditions). Notice that, regions shaded in gray refer to hours in which the building is not occupied (switched off HVAC system, inactive control). Obviously, is such hours the indoor air temperature evolves in accordance with model (2) when $\dot{Q}_{AC} = 0$ (free floating indoor conditions). According to the control design (see Sec. B), when the control system is activated the reference temperature is the output of a suitable designed second order LTI system with an initial output equal to the indoor air temperature at 07:00. This feature is clearly shown in Fig. 6. Here, the time profile of the indoor air temperature subsequent to the controller activation is depicted for the 230-th day of the year. The accurate tracking of the reference temperature obtained by the presented control system is shown in Fig. 7. Here, the time profile of the indoor air temperature is reported in the case of the heavy large-size building in Denver for the 34-th day of the year. Here, it is evident how the reference dynamics are imposed to model (2). In this figure the blue line represents the uncontrolled indoor air temperature occurring before 07.00 (when the HVAC system is switched off).

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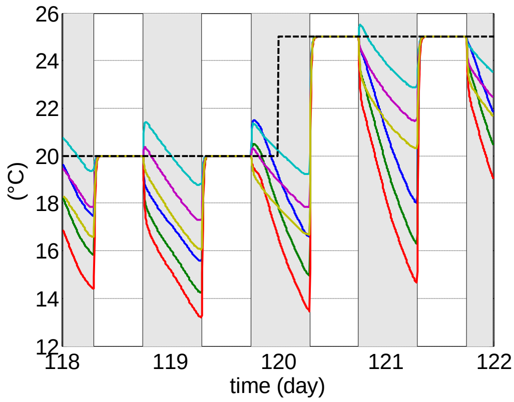

Fig 5: Indoor air temperature for the heavyweight investigated buildings in Denver and Naples. Dashed black line is referred to the set-point indoor air temperature (details about colour lines are reported in Table 4).

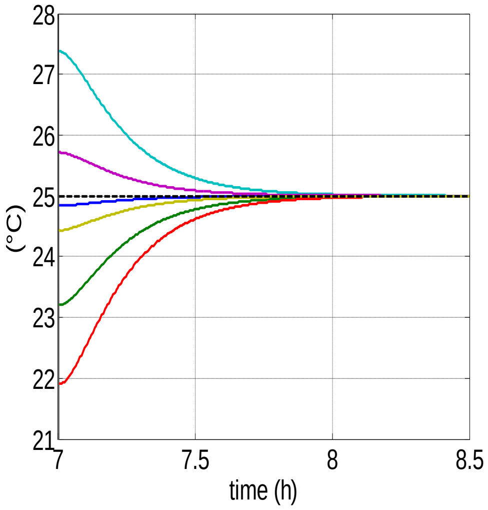

Fig. 6: 230-th day of the year - temperature time profile for the heavyweight investigated buildings in Denver and Naples (details about colour lines are reported in Table 4).

In Fig. 8 the boundedness of the control action (i.e. the sensible thermal load) is reported for all the investigated heavyweight buildings and for the same previously mentioned four sample days. In particular, on the top left side of this figure the control action is reported for the whole year. Note that different heating or cooling loads are obtained as a function of the building typology and weather conditions.

We remark that similar tracking performance was achieved for all the investigated case studies (the remaining time histories are omitted for sake of brevity). The effectiveness of the control method to precisely impose temperature profiles can be detected also by Table 5. Here, the temperature mean squared error for the entire year and for all the 48 developed case studies is reported.

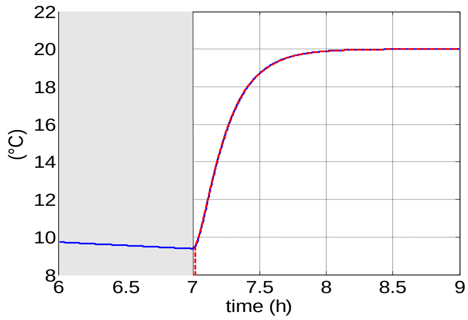

Fig. 7: 34-th day of the year - temperature time profile for the heavyweight mall building in Denver.

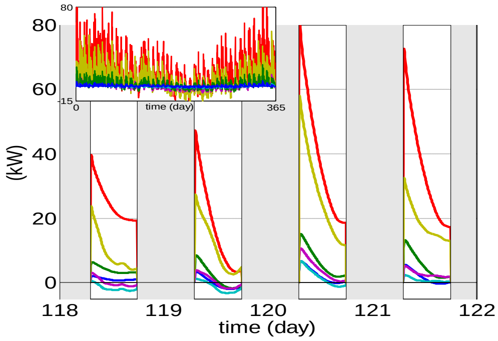

Fig. 8: Sensible thermal load (control action) for the heavyweight investigated buildings in Denver and Naples (details about colour lines are reported in Table 4).

Table 5: temperature means squared error over the year (in °C).

Location	Building					
	Small-size		Middle-size		Large-size	
	Light	Heavy	Light	Heavy	Light	Heavy
Denver	0.02	0.017	0.028	0.023	0.0257	0.0254
Naples	0.018	0.018	0.027	0.022	0.035	0.0278
Rome	0.025	0.0159	0.0292	0.0243	0.037	0.031
Milan	0.019	0.016	0.0243	0.0251	0.0324	0.0294
Athens	0.02	0.0182	0.0267	0.024	0.0352	0.035
Freiburg	0.023	0.0176	0.0247	0.0271	0.038	0.032
Copenhagen	0.018	0.015	0.026	0.0293	0.041	0.029
Nice	0.019	0.018	0.0245	0.0232	0.0357	0.031

Notice that for each indoor air set-point temperature imposed to the heating and cooling building simulation model, the resulted control action (i.e. the sensible load) can be exploited for obtaining the related yearly heating and cooling energy demands. Such information could be of a great interest for building designers and practitioners. In particular, Fig. 9 and Fig. 10 report the winter heating demand for the investigated light and heavy buildings (dwelling, office and mall), respectively. As it is possible to observe, the amount of

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yearly heating demand strongly depends on the occurring Heating Degree Day (HDD): the higher the HDD the higher the heating requirements. Furthermore, as expected, the heavier the envelope, the higher the heating demand. Analogously, Fig. 11 and Fig. 12 show the yearly summer cooling demands for the light and heavyweight buildings, respectively. In summer, as expected, the heavier the building envelope, the lower the cooling demands. Obviously, for all the investigated case studies, the highest heating demands are obtained for the large size (mall) building. The opposite occurs for the cooling demands. These results are due to the same internal gains per square meter of building floor assumed in all the cases. Such hypothesis was taken into account in order to analyse the only effects of the building geometry and weather conditions on the heating and cooling buildings performance. Of course, the higher the heated (cooled) volume, the higher (the lower) the related demands.

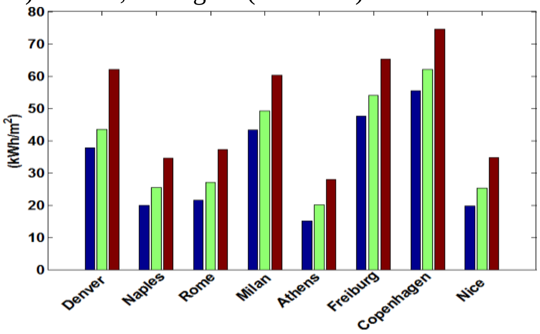

Fig. 9: Yearly winter heating demand for lightweight buildings, small-size (blue bar), middle-size (green bar) and large-size (red bar).

As, expected, among all the analysed weather zones and for all the investigated buildings, the lowest heating and the highest cooling demands are always obtained in Athens (Mediterranean climate). The highest heating and the lowest cooling demands are always obtained in Copenhagen (highest HDD among the investigated weather zones). Finally, in Fig. 13 and Fig. 14, the calculated heating and cooling peak loads for all the investigated case studies are reported. Notice that for sake of brevity only the results related to the heavyweight building envelopes are shown. Here, it is possible to observe that the heating peak loads are much higher than the cooling ones. This is due to: i) the very low internal gains assumed for all the case studies; ii) the selected weather conditions (disturbances).

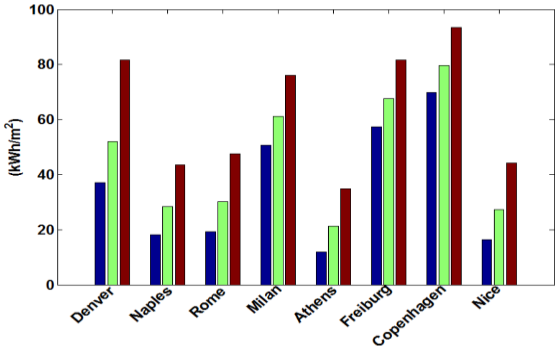

Fig. 10: Yearly winter heating demand for heavyweight buildings, small-size (blue bar), middle-size (green bar), large-size (red bar).

While the highest cooling load is obtained also in this case in Athens, the highest heating one is observed in Denver (and not in Copenhagen). Thus, the worst winter condition is obtained in Denver. Here, a cold clear winter and a hot dry summer is observed as well as large diurnal temperature variations throughout the year. Also such results can be useful for building designers.

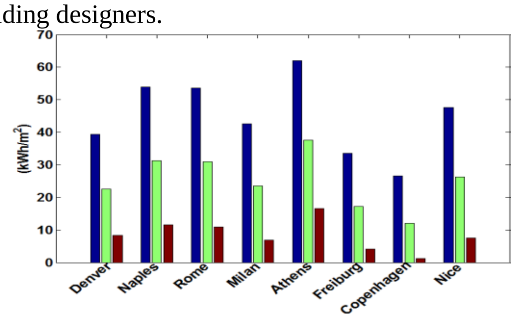

Fig. 11: Yearly summer cooling demand for light buildings, small-size (blue bar), middle-size (green bar) and large-size (red bar).

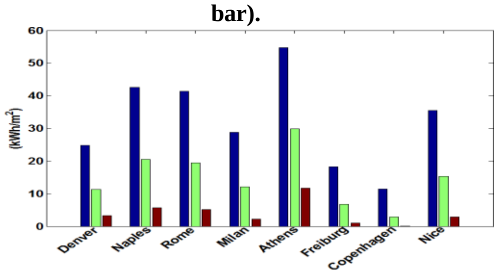

Fig. 12: Yearly summer cooling demand for heavy buildings, small-size (blue bar), middle-size (green bar) and large-size (red bar).

Concerning plant disturbances, the winter outdoor air temperatures T_{out} resulted to be the most predominant among those taken into account. In fact T_{out} is almost always and everywhere lower than the selected indoor air set point of 20°C. It must be also noted that during summer T_{out} is averagely close to the indoor air temperature set-point, which in the investigated case studies was fixed equal to 25°C. During such season and especially in Mediterranean weather zones, remarkable plant disturbances are caused also by sun radiation.

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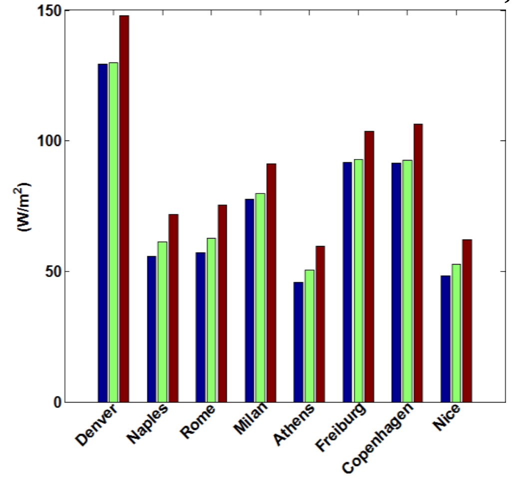

Fig. 13: **Heating peak loads for heavy buildings, small-size (blue bar), middle-size (green bar) and large-size (red bar).**

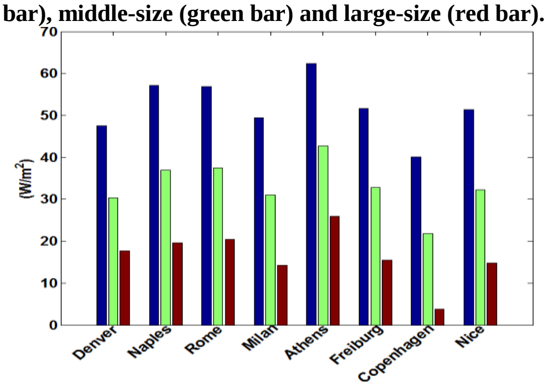

Fig. 14: **Cooling peak loads for lightweight buildings, small-size (blue bar), middle-size (green bar) and large-size (red bar).**

VI. CONCLUSION

In this paper we propose a PI control scheme with optimal control gains for controlling the indoor air temperature of buildings. Through such scheme, the selected PI control gains guarantee the minimization of a quadratic cost function of temperature tracking error and thermal sensible load. Since the resulting optimization problem cannot be solved in closed form, an iterative numerical scheme is here proposed. In addition, the control and the tuning approach presented in this paper were implemented in a software module included in the novel version of a modular building energy performance simulation code (DETECt), previously developed by the authors. Both the novel control scheme and the tuning algorithm represent one of the main enhancements of such dynamic simulation code developed for the prediction of building heating and cooling requirements and loads. The effectiveness of the tuning procedure and the resulting control action on imposing temperature profiles was also tested on a wide range of case studies related to several buildings of different geometry and construction materials, subjected to different weather conditions. In general, through the simulation results interesting guidelines, useful for building energy designers and practitioners, can be obtained.

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AUHTOR'S PROFILE

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Stefania Santini (M.Sc.) received the degree in electronic engineering and the Ph.D. degree in automatic control from University Federico II, Naples, Italy, in 1996 and 1999, respectively. Her Ph.D. research work was supported by the Engine Institute of the National Research Council. Since 2001, she has been an Assistant Professor of Automatic Control in the Department of Electrical Engineering and Information Technology. Her research interests are in the area of the analysis and control of nonlinear systems with applications to automotive engineering, transportation technologies and, more recently, computational biology. She is involved in many projects with industry including SMEs operating in the automotive field.