Cost-optimal building thermal design in presence of multi-objective model predictive control for energy systems

Fabrizio Ascione\textsuperscript{a}, Nicola Bianco\textsuperscript{b}, Claudio De Stasio\textsuperscript{c}, Gerardo Maria Mauro\textsuperscript{d} and Giuseppe Peter Vanoli\textsuperscript{e}

\textsuperscript{a} University of Naples Federico II, Naples, Italy, fabrizio.ascione@unina.it
\textsuperscript{b} University of Naples Federico II, Naples, Italy, nicola.bianco@unina.it
\textsuperscript{c} University of Naples Federico II, Naples, Italy, claudio.destasio@unina.it
\textsuperscript{d} University of Naples Federico II, Naples, Italy, gerardomaria.mauro@unina.it (CA)
\textsuperscript{e} University of Sannio, Benevento, Italy, vanoli@unisannio.it

Abstract:
A novel methodology is proposed in order to support the cost-optimal design of building envelope’s thermal characteristics and space conditioning systems in presence of an enhanced simulation-based model predictive control (MPC) for heating and cooling operations. The cost-optimal solution is identified by running a main mono-objective genetic algorithm (GA) that allows to minimize the global cost for space conditioning over building lifecycle. Each solution investigated by the GA represents a building thermal design combined with the MPC of space conditioning systems. In order to define the MPC strategy, the main mono-objective GA launches two secondary bi-objective GAs that optimize the heating and cooling operations, respectively. These secondary GAs perform a Pareto optimization by minimizing operating cost for space conditioning and thermal discomfort. They provide the optimal values of hourly set point temperatures for heating and cooling systems, with a day-ahead planning horizon, by considering the forecasts of weather conditions and building use. The optimal control strategy is detected based on needs and wills of users, who set a minimum level of thermal comfort to be fulfilled. The three employed GAs are implemented by coupling MATLAB® (optimization engine) with EnergyPlus (building performance simulation tool). For testing purposes, the methodology is applied for the thermal design of a new multi-zone residential building located in Naples (Southern Italy). It produces potential savings of 35.4 kWh/m\textsuperscript{2}a as for primary energy consumption, and of around 7'000 € as for global cost, by ensuring the same satisfying comfort level, compared to standard approaches for building thermal design and space conditioning systems’ control.

Keywords:
Building simulation-based optimization, Building thermal design, Model predictive control, Multi-objective optimization, Genetic algorithms, Cost-optimal analysis.

1. Introduction and State-of-the-art
The efficient energy design of buildings is definitely a strong weapon that we must use in order to fight for a sustainable development and for a green world [1]. However, it is an extremely complex issue that involves several decision variables, such as the sundry characteristics of building envelope and HVAC (heating, ventilating and air-conditioning) systems, and objective functions, such as the minimization of energy consumption [2], financial expenditure [3], polluting emissions [4] and indoor thermal discomfort [5]. These goals are linked to two main perspectives, which are generally divergent: the collective (state) one, pursuing the minimization of the environmental impact, and the private (single building) one, pursuing the maximization of the financial benefit [6]. The Energy Performance of Buildings Directive (EPBD) recast (2010/31/EU) [7] tries to harmonize such perspectives by prescribing the cost-optimal analysis to address building energy design, as detailed in the Delegated Regulation (EU) No. 244/2012 [8]. This analysis aims at the detection of the cost-optimal solution [9], which minimizes the global cost, related to investment and operation, of energy uses over building lifecycle. Since a huge amount of energy uses is due to space conditioning, this study is focused on building thermal design, and thus on primary energy consumption for microclimatic control (PEC) and associated global cost (GC). The purpose is to identify the building thermal design that minimizes GC by applying a rigorous cost-optimal analysis, which investigates a
proper number of design scenarios by assessing the values of PEC and GC. The outcome is the cost-
optimal curve that represents GC in function of PEC for all explored scenarios, and the minimum of
the curve provides the cost-optimal design. Definitely, the cost-optimality is a powerful tool that
produces a compromise solution between the mentioned collective and private perspectives. Indeed,
compared to standard approaches for building thermal design, it implies significant reductions of
energy consumption, and thus polluting emissions, by minimizing, at the same time, the financial
expenditure of the private. Nevertheless, the implementation of the cost-optimal analysis features a
crucial issue, due to the computational complexity. In this regard, a rigorous assessment of cost-
optimality requires to simulate a huge number of thermal design scenarios, by means of reliable BPS
(building performance simulation) tools. These tools, such as EnergyPlus [10], TRNNSYS [11], ESP-
r [12] and IDA ICE [13], perform dynamic energy simulations that need significant running times,
and therefore a robust cost-optimal analysis requires a high computational burden. This issue can be
faced by employing proper building performance optimization (BPO) algorithms [14] that reduce the
number of investigated solutions, through a ‘smart research’ managed by the optimization logic. The
BPO is generally based on the combination between a BPS tool, which predicts building energy
performance, and an optimization engine, which runs the optimization algorithm [15]. Several
algorithms can be used, such as derivate-based or derivative-free, deterministic or stochastic, single-
objective or multi-objective. Since the BPS tools normally operate as a black box, they do not provide
a differentiable objective function to be minimized or maximized. Thus, derivative-free optimization
methods [16] are generally employed for BPO. This leads to numerical (or simulation-based)
optimization [15], which consists of an iterative procedure that determines the improvement of the
solution, iteration by iteration, until a sub-optimal solution is achieved (the ‘true optimum’ is
generally unknown) [17, 18]. Among derivative-free algorithms, genetic algorithms (GAs) are the
most popular for BPO [19], because they can easily handle black box functions, they normally do not
converge to local minima, they allow both mono- and multi-objective optimizations. GAs are based
on the ‘darwinian’ evolution of a population of individuals (i.e., solutions), by simulating the
processes of selection, crossover and mutation, thereby providing the optimal solution after a
sufficient number of generations (i.e., iterations). GAs have been widely adopted for the optimization
of building energy performance, in most cases with a multi-objective approach [2-5, 19-23] which is
more proper for BPO because various divergent objective functions subsist [24, 25]. Furthermore,
they have been employed to support a robust cost-optimal analysis of building energy design [3, 19],
by yielding significant savings of computational times compared to standard approaches.
However, in order to achieve a thorough optimization of energy performance, a proper and cost-
optimal building thermal design is not sufficient, but it must be followed by the optimization of the
HVAC system operation through effective control strategies, which can produce significant energy
savings [26, 27]. In this regard, a very promising technique consists of model predictive control
(MPC) procedures, which have had a widespread diffusion in the last years [28, 29]. The MPC of
HVAC system operation is based on the predictions of building energy demand for space
conditioning, over a planning horizon, depending on the forecasts of weather conditions and
occupancy profiles. Thus, the HVAC system is controlled by taking into account these predictions,
in order to optimize one (or more) objective(s), such as energy consumption, operating cost and
thermal comfort [30]. A day-ahead planning horizon is generally recommended [30-32], because it
implies a good trade-off between forecast reliability and required computational time. The adoption
of effective MPC procedures can imply energy savings in the range 15-50% compared with traditional
control strategies as well as an improvement of thermal comfort, as shown in [30, 33, 34].
Nevertheless, MPC controllers are not easy-to-develop [35], because, likewise a generic BPO routine,
a rigorous MPC procedure requires the combination between a BPS tool, for the prediction of energy
demand, and an optimization engine, for the detection of the optimal HVAC system operation [30,
32, 36]. This coupling produces the simulation-based MPC. The adoption of reliable, but
computationally-expensive, BPS tools [10-13], is fundamental for an accurate prediction of building
energy behaviour, and thus for the success of MPC strategies [37]. On the other end, the
implementation of proper optimization algorithms, such as GAs, is fundamental to perform a ‘smart
research’ of the possible HVAC system operation scenarios, thereby achieving the optimal solution with adequate computational times, which obviously must not exceed the planning horizon.

Finally, the optimization of building energy performance requires both the proper building design and the efficient operation of HVAC systems. Most studies provided by current scientific literature faced these crucial issues separately, as shown in the above literature review. Conversely, this paper handles both issues with an original integrated approach. A novel methodology is proposed in order to support the cost-optimal building thermal design in presence of a simulation-based MPC strategy for space heating and cooling operations. Notably, the building thermal design concerns the thermal characteristics of building envelope and the type of HVAC systems. The cost-optimal solution is identified by a main mono-objective GA that minimizes the global cost for space conditioning over building lifecycle. Each solution investigated by the GA represents a building thermal design in presence of the mentioned MPC strategy. In this regard, the employed MPC procedure has been already proposed by the same authors in [30] concerning space heating operation, and it is here enhanced in order to consider space cooling too. This procedure is based on the implementation of a bi-objective GA that performs the Pareto optimization of operating cost for space conditioning and thermal discomfort. It provides the optimal values of hourly set point temperatures, with a 24-h day-ahead planning horizon, by considering the forecasts of weather conditions and occupancy profiles and by fixing a maximum level of acceptable discomfort. Thus, in order to define the MPC strategy, the main mono-objective GA launches two secondary bi-objective GAs that optimize the heating and cooling operations, respectively. The three employed GAs are implemented by coupling EnergyPlus, that is the BPS tool, with MATLAB® [38], that is the optimization engine. For testing purposes, the methodology is applied to a new multi-zone residential building located in Naples (Southern Italy).

2. Methodology

The proposed methodology performs a multi-stage and multi-objective optimization in order to detect the cost-optimal building energy design in presence of a model predictive control (MPC) strategy for space heating and cooling operations. It can be applied to new or existing buildings, but, definitely, it is more proper and effective for new constructions because there are no rigid constraints in the selection of the explored design scenarios, and therefore the potential benefits are higher. The optimization procedure is run by coupling EnergyPlus and MATLAB®, which communicate through a coupling function written in MATLAB®. EnergyPlus is employed as BPS tool because it represents the most popular whole building energy simulation program for BPO [15] by virtue of its high reliability and accuracy in energy predictions. MATLAB® is employed as optimization engine, because it allows to run mono- and multi-objective GAs, it can automatically launch EnergyPlus and handle text-based EnergyPlus inputs and outputs through the developed coupling function.

In the next subsections the methodology is detailed:

- Section 2.1 shows the formulation of the optimization problem that represents the research question on which the methodology is based;
- Section 2.2 describes the algorithms (GAs) employed to solve the optimization problem;
- Section 2.3 elucidates the methodology framework by showing how the algorithms (described in section 2.2) are employed to solve the optimization problem (described in subsection 2.1).

2.1. Formulation of the optimization problem

The research question of the study regards the detection of the cost-optimal building thermal design. Therefore, the main objective function to be minimized is the global cost for space conditioning over building lifecycle (GC), as defined in [7, 8]. GC is assessed by means of MATLAB® post-process that handles the outputs of EnergyPlus simulations, by following the procedure delineated in [8]. The building thermal design concerns the parameters that represent the thermal characteristics of the building envelope as well as the features of the HVAC systems. These parameters are the design variables of the main optimization problem, which are assumed as discrete in order to limit the investigated domain thereby reducing the required computational burden. In this regard, the use of
The main optimization problem is coupled with two secondary optimization problems addressed to the model predictive control (MPC) of space heating and cooling operations, respectively. Indeed, each solution concerning building thermal design includes the implementation of a simulation-based MPC strategy for HVAC systems’ regulation, which employs the procedure proposed by the authors in [30] for heating operation, and here enhanced by considering also space cooling. The MPC procedure is based on the optimization of the hourly set point temperatures in the building thermal zones, over a 24-h day-ahead planning horizon, by minimizing energy cost and thermal discomfort. In this regard, the building energy behaviour is predicted by running EnergyPlus simulations that exploits, as inputs, the hourly forecasts of weather conditions and occupancy profiles. Therefore, the achievement of the MPC strategy requires to solve a bi-objective optimization problem, day-to-day. The two conflicting objective functions to be minimized are: I) the daily operating cost for space conditioning (OC) and II) the maximum hourly value of the predicted percentage of dissatisfied (PPD\textsuperscript{max}), based on Fanger comfort theory [39], over the day. The design variables are the hourly values of set point temperatures in the building thermal zones, which delineate the daily HVAC operation. Each of them is encoded by a string of 2 bits, so that it can assume 4 different discrete values. These strings of bits, which provide the 24-h HVAC control strategy, are included in the vector \( \mathbf{x}_h \) concerning heating operation and in the vector \( \mathbf{x}_c \) concerning cooling operation. Both vectors have \( 24 \cdot 2 \cdot z \) components, where 24 is the number of hours during the day and \( z \) is the number of thermal zones. Furthermore, there is a constraint because, normally, a time limit subsists for the daily operation of HVAC systems, as established, e.g., by the Italian law [40]. Thus, the operation duration over the day, denoted as \( H \) and expressed in hours, must be lower than the limit \( H_{\text{max}} \). The MPC procedure is implemented for both heating and cooling operations, thereby implying two bi-objective optimization problems. Finally, the main mono-objective optimization problem yields two secondary bi-objective problems, as shown in the following formulation, where the subscripts \( h \) and \( c \) refer to heating and cooling operations, respectively:

Cost-optimal building thermal design = \( \mathbf{x}_{\text{opt}} \)

\[
\mathbf{x}_{\text{opt}} = \mathbf{x} = \arg \min \quad GC(\mathbf{x}, \mathbf{x}_h, \mathbf{x}_c)
\]

subject to:

\[
\mathbf{x} = \begin{bmatrix} x_1, \ldots, x_{n_1}, \ldots, \ldots, x_{(\sum_{i=1}^{N} n_i) - n_{N+1}}, \ldots, x_{\sum_{i=1}^{N} n_i} \end{bmatrix}
\]

with \( x_j = \begin{cases} 0 & \text{for } j = 1, \ldots, \sum_{i=1}^{N} n_i \\ 1 & \text{for } j = 1, \ldots, \sum_{i=1}^{N} n_i \end{cases} \)

\( \mathbf{x}_h = \mathbf{x}_{h,\text{opt}} = \arg \min \int_H (\mathbf{x}, \mathbf{x}_h) = [OC_h(\mathbf{x}, \mathbf{x}_h), PPD_{\text{max}}(\mathbf{x}, \mathbf{x}_h)] \)

subject to:

\( H_h(\mathbf{x}, \mathbf{x}_h) \leq H_{h,\text{max}} \)

with \( x_{h,j} = \begin{cases} 0 & \text{for } j = 1, \ldots, 24 \cdot 2 \cdot z \\ 1 & \text{for } j = 1, \ldots, 24 \cdot 2 \cdot z \end{cases} \)

\( \mathbf{x}_c = \mathbf{x}_{c,\text{opt}} = \arg \min \int_H (\mathbf{x}, \mathbf{x}_c) = [OC_c(\mathbf{x}, \mathbf{x}_c), PPD_{\text{max}}(\mathbf{x}, \mathbf{x}_c)] \)

subject to:

\( H_c(\mathbf{x}, \mathbf{x}_c) \leq H_{c,\text{max}} \)

with \( x_{c,j} = \begin{cases} 0 & \text{for } j = 1, \ldots, 24 \cdot 2 \cdot z \\ 1 & \text{for } j = 1, \ldots, 24 \cdot 2 \cdot z \end{cases} \)
2.2. Optimization algorithms

The main mono-objective optimization problems and the two secondary bi-objective problems are solved by employing a control elitist genetic algorithm (GA), which is variant of NSGA II [41]. This algorithm is a stochastic evaluation-based method, which provides the evolution of a population of individuals (chromosomes) through a series of iterations (generations). It can be applied to both mono- and multi-objective problems. From generation to generation, the population improves, concerning the values assumed by the objective function(s) (rank values), by means of crossover and mutation of the best individuals (parents), detected based on rank value and average crowding distance; the \( c_e \) (elite count) best individuals survive. The children, individuals that originate from crossover, randomly inherit the design variables from the two parents; the fraction of population that derives from crossover is denoted with \( f_c \). The mutated children, individuals that originate from mutation, derive from random parents by assuming a mutation probability of the design variables equal to \( f_m \). The evolution stops when a stop criterion is satisfied, namely either when a maximum number of generations \( (g_{max}) \) is reached or the change in the optimal solution (or Pareto front) between two successive generations is lower than the tolerance \( tol \). The outcome is the optimal solution for the main mono-objective GA (see Table 1) and the Pareto front for the two secondary bi-objective GAs (see Table 2). In the first case, the individuals, encoded by the vector \( x_h \), represent different building thermal designs, whereas, in the second case the individuals, encoded by the vectors \( x_{\text{E}} \) and \( x_{\text{C}} \), represent different control strategies for heating and cooling operations, respectively.

**Table 1. Pseudo-code of the genetic algorithm (GA) for mono-objective optimization**

<table>
<thead>
<tr>
<th>Mono-objective GA</th>
</tr>
</thead>
<tbody>
<tr>
<td>( f \rightarrow ) objective function</td>
</tr>
<tr>
<td>( x \rightarrow ) design variables</td>
</tr>
<tr>
<td>( \tau = 1 ) (generation index)</td>
</tr>
<tr>
<td>Create the initial population ( P^{(1)} = { x_i^{(1)} }_{i=1,...,s} ) of ( s ) individuals</td>
</tr>
<tr>
<td>Calculate ( f(x_i^{(1)}) ) for ( i = 1, \ldots, s )</td>
</tr>
<tr>
<td>Evaluate the rank value and the average crowding distance for each individual of ( P^{(1)} )</td>
</tr>
<tr>
<td><strong>DO UNTIL</strong> at least one stop criterion is satisfied</td>
</tr>
<tr>
<td>( \tau = \tau + 1 )</td>
</tr>
<tr>
<td>Select the parents from ( P^{(\tau-1)} )</td>
</tr>
<tr>
<td>Generate ( P^{(\tau)} = { x_i^{(\tau)} }_{i=1,...,s} ) from crossover and mutation of the parents: elite parents survive</td>
</tr>
<tr>
<td>Calculate ( f(x_i^{(\tau)}) ) for ( i = 1, \ldots, s )</td>
</tr>
<tr>
<td>Evaluate the rank value and the average crowding distance for each individual of ( P^{(\tau)} )</td>
</tr>
<tr>
<td><strong>END</strong></td>
</tr>
<tr>
<td>Return the Optimal solution</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Multi-objective GA</th>
</tr>
</thead>
<tbody>
<tr>
<td>( f \rightarrow ) objective functions</td>
</tr>
<tr>
<td>( x \rightarrow ) design variables</td>
</tr>
<tr>
<td>( \tau = 1 ) (generation index)</td>
</tr>
<tr>
<td>Create the initial population ( P^{(1)} = { x_i^{(1)} }_{i=1,...,s} ) of ( s ) individuals</td>
</tr>
<tr>
<td>Calculate ( f(x_i^{(1)}) ) for ( i = 1, \ldots, s )</td>
</tr>
<tr>
<td>Evaluate the rank value and the average crowding distance for each individual of ( P^{(1)} )</td>
</tr>
<tr>
<td><strong>DO UNTIL</strong> at least one stop criterion is satisfied</td>
</tr>
<tr>
<td>( \tau = \tau + 1 )</td>
</tr>
<tr>
<td>Select the parents from ( P^{(\tau-1)} )</td>
</tr>
<tr>
<td>Generate ( P^{(\tau)} = { x_i^{(\tau)} }_{i=1,...,s} ) from crossover and mutation of the parents: elite parents survive</td>
</tr>
<tr>
<td>Calculate ( f(x_i^{(\tau)}) ) for ( i = 1, \ldots, s )</td>
</tr>
<tr>
<td>Evaluate the rank value and the average crowding distance for each individual of ( P^{(\tau)} )</td>
</tr>
<tr>
<td><strong>END</strong></td>
</tr>
<tr>
<td>Return the Pareto front</td>
</tr>
</tbody>
</table>
2.3. Framework of the optimization procedure

The framework of the proposed methodology, for the assessment of cost-optimal building thermal design in presence of a MPC strategy for space heating and cooling operations, is represented in Fig. 1.

Fig. 1. Framework of the proposed methodology for cost-optimal building thermal design in presence of MPC for space conditioning systems
The shown framework allows to solve the multi-stage and multi-objective optimization problem formulated in subsection 2.1, by implementing the GAs described in subsection 2.2. The optimization routine starts by launching the main mono-objective GA for the detection of the cost-optimal building thermal design. Each individual $x_i$ investigated by this GA, represents a specific configuration of building design combined with the MPC of HVAC systems. Thus, in order to define the MPC strategies for each individual, the main GA launches the two secondary bi-objective GAs that provide the optimal hourly set point temperatures for heating and cooling operations, respectively, over a daily planning horizon. In the real application, the MPC procedure is implemented for each day of the heating and cooling seasons, but, definitely, the proposed methodology cannot investigate all these days because this would imply prohibitive computational times. Therefore, in order to assess the impact of MPC on annual building energy behaviour, the optimal MPC strategy for HVAC operation is assessed for two typical days of heating and cooling seasons, namely the average heating day and the average cooling day. The average heating day is the day that presents the value of primary energy consumption for space heating ($P_{EC_h}$) closest to the average daily value of $P_{EC_h}$ during the heating season. Likewise, the average cooling day is the day that presents the value of primary energy consumption for space cooling ($P_{EC_c}$) closest to the average daily value of $P_{EC}$, during the cooling season. These two typical days have been chosen because the daily values of $P_{EC_h}$, assessed for the average heating day, and $P_{EC_c}$, assessed for the average cooling day, are then exploited to estimate the annual values of $P_{EC_h}$ and $P_{EC_c}$ (and thus of $PEC = P_{EC_h} + P_{EC_c}$) by multiplying them by the number of days of the heating and cooling season, respectively. The same procedure is employed to assess the annual values of $OC$, which are then used to estimate the final goal $GC$. Therefore, for each building design $x_i$, the two secondary GAs allow to detect the optimal MPC strategies for heating and cooling operations. The employed MPC procedure, as detailed in [30], uses a deterministic predictive control concept, by assuming perfect forecasts in a day-ahead horizon. Clearly, in this design phase, the forecasts of weather conditions and occupancy for the average heating and cooling days are not available, and thus they are simulated with the hourly values provided by accredited typical year weather data files and standard schedules of building use, taken from the software DesignBuilder [42]. The procedure is based on the coupling between MATLAB® and EnergyPlus, which is used to predict building energy behaviour in correspondence of different MPC configurations. In standard EnergyPlus simulations, the run period starts from January 1 and ends on the examined day. Conversely, this procedure employs a shorter run period, thereby reducing the required computational burden, which represents one of the main issues of simulation-based MPC methods. In particular, the run period is set equal to the minimum run period ($T^{min}$), which is a characteristic building parameter that represents the minimum number of days that should be covered by energy simulations to obtain reliable results [30]. The value of $T^{min}$ depends on the building typology and can be assessed by implementing the procedure described in [30]. All told, the two bi-objective GAs produce two Pareto fronts, which collect the non-dominated solutions for the MPC of heating and cooling operations, respectively, concerning the mentioned average days. Such solutions minimize $OC$ and $PPD_{max}^h$, as shown in Fig.2 for example purposes (that’s why there are no scales on the axes).

![Pareto Front for MPC of space heating systems](image1)

![Pareto Front for MPC of space cooling systems](image2)

**Fig. 2. Example of the achieved Pareto fronts for the optimization-based MPC of space heating and cooling operations.** The MCDM is performed by fixing a maximum acceptable $PPD_{max}^h$. 

A solution has to be selected from each of the two Pareto fronts by carrying out the so-called multi criteria decision-making (MCDM), which can be performed according to various methods [15]. In this procedure, a maximum acceptable level of $PPD^{MAX}$ is fixed and the solution chosen from each Pareto front is the one that presents a lower value of $PPD^{MAX}$ and minimizes $OC$, as shown in Fig.2. This method for MCDM provides the optimal MPC strategies for space heating and cooling operations, which are encoded by the vectors $x_{h,opt}$ and $x_{c,opt}$, respectively. Then, the value of $GC$ is assessed for each generic individual $x_i$ in presence of the optimized MPC of HVAC operation delineated by $x_{h,opt}$ and $x_{c,opt}$. As aforementioned, $GC$ is assessed in MATLAB® that handles the outputs of EnergyPlus simulations, by following the procedure reported in [8]. $GC$ takes account of investment costs and operating costs for space conditioning ($OC = OC_h + OC_c$). The annual values of $OC_h$ and $OC_c$ are calculated by multiplying the daily values achieved for the average heating and cooling days by the number of days of heating and cooling seasons, respectively. The procedure is repeated for each individual $x_i$ investigated by the main mono-objective GA in order to assess the objective $GC$. For each individual, also the value of $PEC$ is recorded. The optimization routine ends when the stop criterion of the main GA is satisfied, so that the cost-optimal building design is identified. Finally, the procedure provides the cost-optimal curve, reported in Fig.3 for example purposes (that’s why there are no scales on the axes), that depicts the values of $GC$ and $PEC$ for all explored building thermal designs in presence of MPC for HVAC operation. The minimum of the cost-optimal curve represents the cost-optimality.

![Building thermal design: Cost-optimal curve](image)

**Fig. 3. Example of the achieved cost-optimal curve for building thermal design**

### 3. Description of the case study

The methodology is applied for the thermal design of a new multi-zone residential building, located in Naples (Southern Italy), with a mono-storey rectangular geometry, as depicted in Fig. 4.

![Fig. 4. Investigated building: a) rendering and b) plan view with main dimensions and thermal zones](image)
The same building geometry and internal subdivision into thermal zones was investigated by the authors in [30] for the application of the simulation-based MPC of HVAC operation to existing buildings. The building net floor area is 140 \( m^2 \) and the net inner height is 3 m. There are three thermal zones (see Fig. 4 b) with different intended uses and occupancy profiles: a living area, a corridor and a sleeping area. Only the living and sleeping areas are assumed occupied and the related occupancy profiles are reported in Table 4. Thus, the thermal comfort indices, i.e., the values PPD, are assessed only for these two zones. The corridor is assumed as unoccupied because it is a transition zone. However, it is provided with HVAC terminals because the heating or cooling of this zone can exert a strong influence on the other two occupied zones, by operating as thermal buffer. In other words, it highly affects the thermal coupling between the living and sleeping areas, especially in new buildings that are characterized by high levels of envelope thermal insulation. In this regard, the space conditioning of the corridor can be effective, from both energy and comfort perspectives, in some hours of the day, since it increases the heat storage inside the building and reduces the heat transfer between the two occupied main zones [30]. The clothing thermal resistance, which much affects PPD assessment, assumes different values according to accredited standards: in the living zone, it is set equal to 1 \( \text{clo} \); in the sleeping area, it is set equal to 1.3 \( \text{clo} \) from 23:00 to 8:00 for the presence of blankets, and to 1 \( \text{clo} \) from 8:00 to 10:00 because of occupants’ awakening.

| OCCUPIED HOU:
<table>
<thead>
<tr>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>INTERVALS (●)</td>
</tr>
<tr>
<td>0</td>
</tr>
<tr>
<td>LIVING AREA</td>
</tr>
<tr>
<td>CORRIDOR</td>
</tr>
<tr>
<td>SLEEPING AREA</td>
</tr>
</tbody>
</table>

3.1. Options for building thermal design

Different options for the building thermal design are investigated, concerning both the thermophysic characteristics of building envelope and the type of HVAC systems, as shown in Table 4. These options represent the design variables, which are seven (see Table 4), of the main optimization problem, encoded by the vector \( \mathbf{x} \). In all cases, the building structure is in reinforced concrete, with a thermal insulation layer in polyurethane, placed on the external sides of vertical walls, roof and floor on the ground. Materials’ thermal properties are taken from the database of DesignBuilder software [42]. The polyurethane has thermal conductivity \( k \) equal to 0.028 \( \text{W/m K} \), density \( \rho \) equal to 25 \( \text{kg/m}^3 \) and specific heat \( c \) equal to 1300 \( \text{J/kg K} \). Masonry can be in hollow bricks \( k = 0.25 \text{W/m K}; \rho = 750 \text{kg/m}^3; c = 880 \text{J/kg K} \) or lightweight concrete \( k = 0.50 \text{W/m K}; \rho = 1'500 \text{kg/m}^3; c = 880 \text{J/kg K} \), which is definitely characterized by a higher thermal inertia if the thermal transmittance \( (U \text{ value}) \) is the same. Different windows are considered, all with insulated PVC frames. Furthermore, a reference building (RB) is identified, which features the most popular construction practices in the considered geographic zone, that is Southern Italian (typical Mediterranean climate) according to current laws that regulate the energy design of new buildings [43, 44]. The options present in the RB are indicated by bullets in Table 4, which also shows the investment costs \( (\text{IC}) \) of all investigated options for building design, taken partly from [6] and partly from direct quotations of suppliers.
Table 4. Option values and associated investment costs of the design variables related to the thermal characteristics of building envelope and to the HVAC system type (x). The options present in the reference building (RB) are indicated by bullets.

<table>
<thead>
<tr>
<th>DESIGN VARIABLES (DV)</th>
<th>OPTION VALUES</th>
<th>RB INVESTMENT COST (IC)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>(DV1)</strong> Opaque building envelope: Type of envelope and thermal transmittance of vertical walls (U_v), roof (U_r) and floor (U_f)</td>
<td>Concrete frame with insulated (6 cm of polyurethane) hollow blocks: ( U_r = 0.34 \text{ W/m}^2\text{K}; U_f = 0.32 \text{ W/m}^2\text{K}; U_f = 0.40 \text{ W/m}^2\text{K} )</td>
<td>( 40'500 \text{ €} ) (270 €/floor area)</td>
</tr>
<tr>
<td></td>
<td>Concrete frame with highly-insulated (9 cm of polyurethane) hollow blocks: ( U_r = 0.25 \text{ W/m}^2\text{K}; U_f = 0.24 \text{ W/m}^2\text{K}; U_f = 0.28 \text{ W/m}^2\text{K} )</td>
<td>( 42'000 \text{ €} ) (280 €/floor area)</td>
</tr>
<tr>
<td></td>
<td>Insulated (6 cm of polyurethane) lightweight concrete: ( U_r = 0.34 \text{ W/m}^2\text{K}; U_f = 0.32 \text{ W/m}^2\text{K}; U_f = 0.40 \text{ W/m}^2\text{K} )</td>
<td>( 40'500 \text{ €} ) (270 €/floor area)</td>
</tr>
<tr>
<td></td>
<td>Highly-insulated (9 cm of polyurethane) lightweight concrete: ( U_r = 0.25 \text{ W/m}^2\text{K}; U_f = 0.24 \text{ W/m}^2\text{K}; U_f = 0.28 \text{ W/m}^2\text{K} )</td>
<td>( 42'000 \text{ €} ) (280 €/floor area)</td>
</tr>
<tr>
<td><strong>(DV2)</strong> Transparent building envelope: Type of windows, thermal transmittance (U_v), solar heat gain coefficient (SHGC) and visible transmittance (VT). All windows have PVC frames</td>
<td>Double-glazed air-filled with low-emissive coatings: ( U_v = 2.10 \text{ W/m}^2\text{K}; \text{SHGC} = 0.69; \text{VT} = 0.74 )</td>
<td>( 6'182 \text{ €} ) (220 €/window area)</td>
</tr>
<tr>
<td></td>
<td>Double-glazed argon-filled with low-emissive coatings: ( U_v = 1.70 \text{ W/m}^2\text{K}; \text{SHGC} = 0.69; \text{VT} = 0.74 )</td>
<td>( 6'182 \text{ €} ) (220 €/window area)</td>
</tr>
<tr>
<td></td>
<td>Double-glazed air-filled with low-emissive selective coatings: ( U_v = 2.10 \text{ W/m}^2\text{K}; \text{SHGC} = 0.44; \text{VT} = 0.69 )</td>
<td>( 6'744 \text{ €} ) (240 €/window area)</td>
</tr>
<tr>
<td></td>
<td>Double-glazed argon-filled with low-emissive selective coatings: ( U_v = 1.70 \text{ W/m}^2\text{K}; \text{SHGC} = 0.44; \text{VT} = 0.69 )</td>
<td>( 6'744 \text{ €} ) (240 €/window area)</td>
</tr>
<tr>
<td><strong>(DV3)</strong> Absorptance to solar radiation of the external vertical walls: ( a_r )</td>
<td>Clear, and thus cool, paintings: ( a_r = 0.05 )</td>
<td>All options have the same IC, which is therefore not considered</td>
</tr>
<tr>
<td></td>
<td>Medium-Clear paintings: ( a_r = 0.40 )</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Medium-Dark paintings: ( a_r = 0.70 )</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Dark, and thus hot, paintings: ( a_r = 0.95 )</td>
<td></td>
</tr>
<tr>
<td><strong>(DV4)</strong> Absorptance to solar radiation of the roof: ( a_r )</td>
<td>Clear, and thus cool, paintings: ( a_r = 0.05 )</td>
<td>All options have the same IC, which is therefore not considered</td>
</tr>
<tr>
<td></td>
<td>Medium-Clear paintings: ( a_r = 0.40 )</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Medium-Dark paintings: ( a_r = 0.70 )</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Dark, and thus hot, paintings: ( a_r = 0.95 )</td>
<td></td>
</tr>
<tr>
<td><strong>(DV5)</strong> Heating terminals: Type of space heating in-room hydronic terminals</td>
<td>Two-pipe fan coils with water inlet/outlet temperature ( t = 50/45 ^\circ\text{C} )</td>
<td>All options have the same IC, which is therefore not considered</td>
</tr>
<tr>
<td></td>
<td>Hot water radiators with water inlet/outlet ( t = 80/70 ^\circ\text{C} )</td>
<td></td>
</tr>
<tr>
<td><strong>(DV6)</strong> Heating primary system: Type of boiler and nominal efficiency referred to the low calorific value (( \eta ))</td>
<td>Efficient natural gas boiler with ( \eta = 0.95 )</td>
<td>( 2'100 \text{ €} )</td>
</tr>
<tr>
<td></td>
<td>Condensing natural gas boiler with ( \eta = 1.05 ) at water inlet/outlet ( t = 35/55 ^\circ\text{C} )</td>
<td>( 2'500 \text{ €} )</td>
</tr>
<tr>
<td><strong>(DV7)</strong> Cooling primary system: Type of chiller and nominal energy efficiency ratio (EER)</td>
<td>Efficient electrical air-cooled chiller with ( \text{EER} = 2.7 ) at water inlet/outlet ( t = 12/7 ^\circ\text{C} ) and outdoor ( t = 35 ^\circ\text{C} )</td>
<td>( 4'000 \text{ €} )</td>
</tr>
<tr>
<td></td>
<td>Highly-efficient electrical air-cooled chiller with ( \text{EER} = 3.1 ) at water inlet/outlet ( t = 12/7 ^\circ\text{C} ) and outdoor ( t = 35 ^\circ\text{C} )</td>
<td>( 5'000 \text{ €} )</td>
</tr>
<tr>
<td><strong>(DV8)</strong> Combined heating and cooling primary system: Installation of a reversible heat pump</td>
<td>Efficient electrical reversible heat pump with coefficient of performance ( \text{COP} = 3.5 ) in heating operation at water inlet/outlet ( t = 40/45 ^\circ\text{C} ) and outdoor ( t = 7 ^\circ\text{C} ), and ( \text{EER} = 2.7 ) in cooling operation at water inlet/outlet ( t = 12/7 ^\circ\text{C} ) and outdoor ( t = 35 ^\circ\text{C} )</td>
<td>( 7'000 \text{ €} )</td>
</tr>
</tbody>
</table>

The values of IC reported in Table 4 are used in the assessment of global cost (GC). In this regard, the investigation aims to compare different possible building thermal designs with the RB design in order to detect the solution that implies the highest saving of GC, which represents the cost-optimal design. Therefore, there is no need to calculate the absolute value of GC for each design [3], but the GC difference compared to the RB. In this way, if all the option values associated to a design variable have the same value of IC, this investment cost is not considered, as reported in Table 4, because it does not affect the assessment of GC savings, being the same for all building designs (and thus also for the RB).
3.2. Building operation: reference system vs. proposed system

The RB presents a standard strategy for the control of HVAC systems, which is quite popular in buildings of South Italy [30]. In particular, the reference heating system can be turned on from 4:00 to 9:00 and from 18:00 to 23:00, if there is space heating need, thereby implying a maximum daily operation of 10 hours, which represents the maximum daily duration of heating operation \((H_h^{\text{max}}=10)\) in Naples, as prescribed by current Italian law [40]. During these operation intervals, the heating set point temperatures are set equal to 21 °C for all thermal zones. On the other hand, the reference cooling system can be turned on from 10:00 to 20:00 if there is space cooling need, thereby implying a maximum daily operation of 10 hours. In this case, current Italian law does not regulate the maximum daily duration of cooling operation \((H_c^{\text{max}}=24)\). During this operation interval, the cooling set point temperatures are set equal to 25 °C for all thermal zones.

The proposed system implements the proposed MPC strategy for the regulation of HVAC operation. Thus, the operation intervals and the heating/cooling set point temperatures are not set ‘a priori’, but they are provided by the described optimization routine for MPC. The hourly heating set point temperatures can be different from zone to zone and can assume the following four values: 12 °C (heating system switched off), 20 °C, 21 °C, 22 °C. Also the hourly cooling set point temperatures can be different from zone to zone and can assume one of the following four values: 50 °C (cooling system switched off), 24 °C, 25 °C, 26 °C. These values allow to cover a significant range of the possible HVAC operation scenarios [30]. Since each set point temperature can take four values, it is encoded with a string of two bits in the binary space, \(\{00, 01, 10, 11\}\). Since each set point temperature can take four values, it is encoded with a string of two bits in the binary space, \(\{00, 01, 10, 11\}\).

These values allow to cover a significant range of the possible HVAC operation scenarios [30]. Since each set point temperature can take four values, it is encoded with a string of two bits in the binary space, \(\{00, 01, 10, 11\}\). Since each set point temperature can take four values, it is encoded with a string of two bits in the binary space, \(\{00, 01, 10, 11\}\). Since each set point temperature can take four values, it is encoded with a string of two bits in the binary space, \(\{00, 01, 10, 11\}\).

\[ \text{In both reference and proposed systems, the regulation is performed by means of two-way valves, one for each in-zone HVAC terminal, that allow to vary the mass flow rate of supplied hot water. The heating and cooling systems are auto-sized in EnergyPlus.} \]

4. Results and discussion

This section illustrates the results achieved by applying the proposed methodology to the cost-optimal building thermal design of the described case study. The outcomes are based on the following assumptions and observations:

- in the assessment of operating cost for space conditioning \((OC)\), and thus of global cost \((GC)\), the prices of natural gas and electricity have been assumed constant and equal to 0.90 €/Nm\(^3\) and 0.25 €/kWh\(_{el}\), respectively [45];
- the IWEC (international weather for energy calculations) data file available for the city of Naples [46] has been used in EnergyPlus simulations;
- in EnergyPlus simulations, the minimum run period \((T^{\text{min}})\) has been employed; this has been assessed for the reference building (RB), described in section 3, according to the procedure developed in [30] and results equal to 10 days;
- for the assessment of the annual values of primary energy consumption for space conditioning \((PEC)\), \(OC\) and \(GC\), the method based on the average heating and cooling days, described in section 2, has been implemented. The average days have been evaluated with reference to the RB and the IWEC data file available for Naples: the average heating day results February 21, while the average cooling day results July 20. They are both weekdays. For the RB, the method of the average days produces a very slight discrepancy compared to annual EnergyPlus simulations, equal to 0.20%; the resulting value of \(PEC_{RB}\) is 48.6 kWh/m\(^2\)a;
- in the multi criteria decision-making (MCDM) related to the bi-objective optimization problems for MPC, the maximum acceptable value of \(PPD^{\text{max}}\) (maximum hourly value of the predicted percentage of dissatisfied over a day in building thermal zones) has been set equal to 20%, which represents the minimum level of thermal comfort recommended by ASHRAE [47];
- the parameters of the three genetic algorithms (GAs) employed in the optimization routine have been set equal to the values reported in Table 5.
Table 5. Control parameters of the three genetic algorithms (GAs)

<table>
<thead>
<tr>
<th></th>
<th>s</th>
<th>$g^{\text{max}}$</th>
<th>$f_c$</th>
<th>$f_m$</th>
<th>$c_e$</th>
<th>tol</th>
</tr>
</thead>
<tbody>
<tr>
<td>Main GA for the Optimization</td>
<td>14</td>
<td>20</td>
<td>0.6</td>
<td>0.1</td>
<td>2</td>
<td>0.001</td>
</tr>
<tr>
<td>of building thermal design</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Secondary GA for MPC</td>
<td>50</td>
<td>50</td>
<td>0.6</td>
<td>0.1</td>
<td>2</td>
<td>0.001</td>
</tr>
<tr>
<td>Optimization of space heating</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>operation ($x_h$)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Secondary GA for MPC</td>
<td>50</td>
<td>50</td>
<td>0.6</td>
<td>0.1</td>
<td>2</td>
<td>0.001</td>
</tr>
<tr>
<td>Optimization of space cooling</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>operation ($x_c$)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Most notably, concerning GAs’ parameters the values of $f_c$, $f_m$, $c_e$, and $tol$ (see subsection 2.2) are equal for the three GAs and have been set according to authors’ expertise and previous studies [5, 19, 30]. On the other hand, the population size ($s$) and maximum number of generations ($g^{\text{max}}$) need a more careful definition that depends on the features of the optimization problems. Indeed, $s$ and $g^{\text{max}}$ highly affect convergence and reliability of the GAs. In this regard, several previous studies [2-5, 19-23], about the optimization of building energy design, employed $s$ values included in the range $2 – 6$ times the number of design variables, and $g^{\text{max}}$ values included in the range $20 – 100$ generations. Therefore, in this study, by considering the high computational burden due the simultaneous running of three GAs, the values of $s$ and $g^{\text{max}}$ of the main GA, aimed at detection of the cost-optimal building design, have been set equal to the minimum values provided by the aforementioned reliable ranges. Thus, $s$ has been set equal to 14, two times the number of the (seven) design variables, and $g^{\text{max}}$ has been set equal to 20. On the other hand, concerning the use GAs for simulation-based MPC of HVAC systems, the same authors showed that the reliable values for $s$ and $g^{\text{max}}$ are both equal to 50 [30], which have been, thus, used in the two secondary GAs, aimed at the detection of the MPC strategies.

All told, the running of the optimization routine, described in section 2, yields the cost-optimal curve of building thermal energy design depicted in Fig. 5. The cost-optimal solution is characterized by:

- opaque building envelope composed of insulated (6 cm of polyurethane) lightweight concrete with $U_v = 0.34 \text{ W/m}^2\text{K}$, $U_r = 0.32 \text{ W/m}^2\text{K}$, $U_f = 0.40 \text{ W/m}^2\text{K}$;
- transparent building envelope composed of double-glazed air-filled windows with low-emissive coatings, with $U_w = 2.10 \text{ W/m}^2\text{K}$, $\text{SHGC} = 0.69$ and $VT = 0.74$;
- medium-clear external vertical walls with $\alpha_v = 0.40$;
- clear (i.e., cool) roof with $\alpha_r = 0.05$;
- hot water radiators as heating terminals with water inlet/outlet $t = 80/70 ^\circ \text{C}$;
- efficient natural gas boiler with $\eta = 0.95$;
- efficient electrical air-cooled chiller with $EER = 2.7$.

![Cost-optimal analysis of building thermal design](image)

Fig. 5. Cost-optimal curve for building thermal design provided by the optimization routine: Detection of the cost-optimal solution
The described solution provides a $PEC$ of 13.2 kWh/m$^2$a and is consistent with energy considerations. Indeed, concerning the opaque building envelope, the lightweight concrete is preferred to the hollow bricks because it ensures higher thermal inertia of the masonry, which allows a major exploitation of the MPC strategies for HVAC operation, and thus larger potential energy savings. Both opaque and transparent envelopes present values of thermal transmittance in line with current Italian prescriptions for new buildings [43]. A higher level of insulation is avoided because it would imply a drastic increase of cooling demand and the risk of indoor overheating [6, 7, 19], thereby producing a worsening of annual energy performance. About the radiative properties of vertical walls, roof and windows, it should be noted that in wintertime the solar radiation is less perpendicular, and thus it mostly impacts on vertical walls and windows. Therefore, windows’ selective coatings are not implemented because the negative impact on heating demand would be more significant than the positive impact on cooling demand. Likewise, the vertical walls’ external plasters have solar absorptance equal to 0.4, which yields a good compromise between heating and cooling needs. Conversely, in summertime the solar radiation is more perpendicular and thus it mostly impacts on the roof. Therefore, the implementation of a cool roof is extremely effective, because the positive impact on cooling demand is much higher than the negative impact on heating demand. Concerning the HVAC system, hot water radiators are preferred to fan coils as heating terminals for two main reasons. First, they have a higher heat storage capability, and thus thermal inertia, which allows a major exploitation of MPC as aforementioned. Secondly, they ensure higher thermal comfort levels because they imply an increase of surfaces’ mean radiant temperature. Radiators require hot water at around 80 °C, and thus the efficient natural gas boiler is preferred to condensing boiler and heat pump, because the performance of these latter systems drastically worsen when operating with high temperatures. Finally, the efficient air-cooled chiller ($EER = 2.7$) is more cost-effective than the high-efficient one ($EER = 3.1$) because the MPC produces a very low cooling demand, and therefore the potential energy benefits produced by highly-efficient systems do not justify the initial investment.

Fig. 6. Pareto fronts for the optimization-based MPC of space conditioning systems in presence of the cost-optimal solution: heating operation (a) and cooling operation (b). The optimal solutions, by setting a limit value of $PPD^{\text{max}}$ equal to 20%, are highlighted.
Fig. 6 shows the two Pareto fronts provided by the two secondary bi-objective GAs for the MPC of heating (Fig. 6a) and cooling (Fig. 6b) operations, respectively, in correspondence of the described cost-optimal building thermal design. The MCDM has allowed to select two non-dominated solutions from the two Pareto fronts, by fixing a limit value of $PPD^{\text{max}}$ equal to 20%, as highlighted in Fig. 6. These solutions provide the optimal MPC strategies, depicted in Fig. 7, concerning:

- the heating operation during the average heating day, encoded by the vector $x_{\text{h,opt}}$ (see Fig. 7a);
- the cooling operation during the average cooling day, encoded by the vector $x_{\text{c,opt}}$ (see Fig. 7b).

![Fig. 7. Optimal MPC strategy in presence of the cost-optimal solution by setting $PPD^{\text{max}}$ equal to 20%: heating operation during the average heating day (a) and cooling operation during the average cooling day (b). When the HVAC system is switched off, set point temperatures are not reported.](image)

The outcomes of Fig. 7 comply with thermo-physical considerations by fulfilling the forecasts of occupancy profiles (Table 3) and weather conditions (IWE data file). Globally, the HVAC terminals are switched on in the living and sleeping areas when these zones are occupied. The operation is intermittent in order to cover a wide period by exploiting the high building thermal inertia. In some hours, the HVAC terminals are switched on also in the corridor, even if this is considered unoccupied. This is effective because implies a reduction of the heat transfer between the two occupied thermal zones, which are conditioned in different periods of the day, and thus the corridor works as a thermal buffer. Furthermore, the corridor space conditioning allows to store heat inside the building, by exploiting the high level of thermal insulation, at a low energy cost because of the small size of the corridor compared to the other two zones. As clear in Fig. 7, the HVAC operation follows also the trend of predicted external temperature and occupants’ clothing. For instance, when a reduction of external temperature is predicted, the heating set point temperatures increase, as occurs in the interval 15:00-16:00 as for the corridor heating (see Fig. 7a). Likewise, the heating system is switched on in the sleeping area from 15:00 to 16:00, because of occupants’ awakening that causes a reduction of clothing thermal resistance (blankets are taken off). Moreover, the cooling system is always switched off during nighttime because external temperature is quite low (see Fig. 7b), and thus there are no cooling needs.

Finally, it is noted that also the reference HVAC system, present in the RB, implies a maximum value of $PPD^{\text{max}}$ close to 20% for both average heating and cooling days. Thus, compared to the RB, the
cost-optimal solution provided by the developed methodology yields potential savings of 35.4 kWh/m²a (72.8 %) as for PEC, and of around 7’000 € as for GC, by ensuring the same satisfying comfort level. It is noted that such savings have been calculated by using the method of the average heating and cooling days (see section 2) for the assessment of PEC and GC, concerning both reference building (as is) and retrofitted building configurations, as mentioned at the beginning of this section.

5. Conclusions
The Energy Performance of Buildings Directive (EPBD) recast (2010/31/EU) prescribes the cost-optimal analysis to support an energy-efficient and cost-effective building design. However, a proper design is not sufficient to achieve a thorough optimization of building energy performance, because a deep attention must be paid to the regulation of HVAC system operation through effective control strategies. The paper faces these correlated issues by proposing a novel integrated methodology.

The methodology allows to detect the cost-optimal building thermal design, in presence of an enhanced simulation-based model predictive control (MPC) strategy for space heating and cooling operations. The building thermal design concerns envelope’s thermal characteristics and HVAC systems’ types. The cost-optimal solution is identified by running a main mono-objective genetic algorithm (GA), and each explored solution represents a building thermal design combined with the mentioned MPC for space conditioning systems. In order to define the MPC strategy, the main mono-objective GA launches two secondary bi-objective GAs that provide the optimal hourly values of set point temperatures for heating and cooling operations, respectively, by minimizing operating cost and thermal discomfort. The optimal control solutions are taken from the Pareto fronts, by fixing a minimum level of required comfort. The three employed GAs are implemented by coupling MATLAB® (optimization engine) with EnergyPlus (BPS tool). The MPC procedure operates with a 24-h day-ahead planning horizon, by considering the forecasts of weather conditions and building use. The high computational time required by simulation-based MPC procedures is reduced by using a minimum reliable run period in energy simulations, and by properly setting the GAs’ parameters.

The optimal control strategy is assessed for two typical days of heating and cooling seasons, respectively, namely the average heating day and the average cooling day. These two days are characterized by a primary energy consumption for space conditioning (PEC) approximately equal to the average daily values of PEC during the heating and cooling seasons, respectively. The daily values of PEC assessed for the average days are exploited to estimate the annual values, by considering the number of heating and cooling days during the year. The same procedure is employed to assess the operating costs, which are then used to estimate the global cost for space conditioning over building lifecycle (GC). The final outcome of the proposed procedure is the cost-optimal building thermal design, which minimizes GC, and the optimal MPC strategy for the operation of the HVAC system concerning the average heating and cooling days.

As case study, the methodology has been applied to a new multi-zone residential building located in Naples (Southern Italy). The detected cost-optimal building thermal design is characterized by:

- opaque building envelope composed of insulated (6 cm of polyurethane) lightweight concrete with thermal transmittance ($U$) of vertical walls, roof and floor equal to $U_v = 0.34$ W/m²K, $U_r = 0.32$ W/m²K, $U_f = 0.40$ W/m²K, respectively;
- transparent building envelope composed of double-glazed air-filled windows with low-emissive coatings, with thermal transmittance $U_w = 2.10$ W/m²K, solar heat gain coefficient $SHGC = 0.69$ and visible transmittance $VT = 0.744$;
- medium-clear external vertical walls with solar absorptance $a_v = 0.40$;
- clear (i.e., cool) roof with solar absorptance $a_r = 0.05$;
- hot water radiators as heating terminals with water inlet/outlet temperature = 80/70 °C;
- efficient natural gas boiler with efficiency $\eta = 0.95$;
- efficient electrical air-cooled chiller with energy efficiency ratio $EER = 2.7$.

Compared to standard approaches for building thermal design and space conditioning systems’ control, this cost-optimal solution implies potential savings of 35.4 kWh/m²a (72.8 %) as for PEC,
and of around 7’000 € as for GC, by ensuring the same satisfying comfort level. Furthermore, the control strategy of the HVAC system, provided by the MPC procedure for the average heating and cooling days, follows the forecasts of weather conditions and occupancy and complies with thermo-physical considerations.

Finally, the proposed methodology implies a double potential benefit: a benefit for the collectivity, due to PEC reduction that yields a reduction of polluting emissions and therefore of building environmental impact; a benefit for the private, due to GC savings. This is a step toward sustainability.

**Nomenclature**

- $a$: absorptance to solar radiation
- $COP$: coefficient of performance of heat pumps
- $c_e$: elite count of the GA
- $f$: objective functions
- $f_c$: crossover fraction of the GA
- $f_m$: mutation probability of the GA
- $EER$: energy efficiency ratio of electric chillers
- $GC$: global cost for space conditioning, €
- $g^{max}$: maximum number of generations of the GA
- $H$: hours of daily operation of the HVAC system, h
- $H^{max}$: maximum number of hours of daily operation of the HVAC system, h
- $IC$: investment cost, €
- $N$: number of decision variables
- $n_i$: number of bits encoding the i-th decision variable
- $OC$: operating cost for space conditioning, €/day
- $PEC$: primary energy consumption for space conditioning, %
- $PPD$: predicted percentage of dissatisfied, %
- $PPD^{max}$: maximum hourly value of PPD over a day in building thermal zones, %
- $SHGC$: solar heat gain coefficient
- $s$: population size of the GA
- $T^{min}$: minimum run period, days
- $t$: temperature, °C
- $tol$: tolerance concerning the stop criterion of GAs
- $U$: thermal transmittance of opaque components, W/m²K
- $U_w$: thermal transmittance of windows, W/m²K
- $VT$: visible transmittance
- $x$: vector of bits encoding the decision variables
- $x_c$: vector of bits encoding the operation, i.e., set point temperatures, of the space cooling system
- $x_h$: vector of bits encoding the operation, i.e., set point temperatures, of the space heating system
- $z$: number of building thermal zones

**Greek symbols**

- $\eta$: energy efficiency referred to the low calorific value of boilers

**Subscripts and superscripts**

- $c$: space cooling
- $f$: floor
Abbreviations

BPO building performance optimization
BPS building performance simulation
GA genetic algorithm
HVAC heating, ventilating and air-conditioning
MCDM multi criteria decision-making
MPC model predictive control
RB reference building

References

[12] ESP-r, Available at: <http://www.esru.strath.ac.uk/Programs/ESP-r.htm>.
[44] Italian Government, Decree (Decreto Legge 4 Giugno 2013, n°63). Disposizioni urgenti per il recepimento della Direttiva 2010/31/UE del Parlamento europeo e del Consiglio del 19 maggio 2010, sulla prestazione energetica nell’edilizia per la definizione delle procedure d’infrazione avviate dalla Commissione europea, nonché’ altre disposizioni in materia di coesione sociale. [in Italian]