Decision support methodologies and day-ahead optimization for smart building energy management in a dynamic pricing scenario

https://doi.org/10.1016/j.enbuild.2020.109963

Decision support methodologies for energy management in a Dynamic Pricing Scenario

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Abstract

Nowadays identifying techniques aimed at a rational use of electric power has become even more important than the production of energy itself. This is caused by different factors, as the progressive saturation of the Italian electricity grid, which is increasingly subject to connection requests, mainly due to the development of plants which exploit renewable energy sources. This work suggests a new approach based on the combination of the optimizer and the simulator developed in the MATLAB/Simulink environment, in order to reduce the energy costs in buildings during the summer while taking into consideration the user comfort. The electrical consumption of the entire building is taken into consideration is here examined with the aim of applying an air-conditioning system. The goal is to find, the day before,which is the optimal hourly scheduling of the set points that must be applied the next day, taking into consideration all external conditions; weather conditions and the hourly energy price. In order to achieve this objective, the control variables, that have been changed, are the room temperature set points and the flow water temperature set point. As required by the UNI EN ISO 7730:2006 standard, comfort measurement was calculated with the PPD (Predicted Percentage of Dissatisfied) index. Different scenarios were investigated as well. The results show that there is an aver-

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https://doi.org/10.1016/j.enbuild.2020.109963

age of 16-17% potential cost saving, while maintaining a high level of comfort. The study was carried out by simulating a real office building in Italy, and the comparisons are shown regarding the actual settings applied to it.

Keywords: Optimization, Simulation, Energy cost,

1. Introduction

The building sector is the biggest/most important user of energy and CO_2 emitter in the European Union (EU) and is responsible for about 40% of the EU's total final energy consumption and CO_2 emissions. As a consequence, the cornerstone of the European energy policy has an explicit orientation to the conservation and rational use of energy in buildings as the energy performance of building directive (EPBD) 2002/91/EC and its recast (EPBD) 2010/31/EU indicate [8] [9] . The EPBD's main objective is to promote the cost-effective improvement of the overall energy performance of buildings. In Europe, member states have set an energy savings target of 20% by 2020 and 27% by 2030, mainly through energy efficiency measures. A number of methodologies for optimizing real-time performance, automated fault detection and isolation were developed in IEA-Annex 25 [10]. Moreover, amongst worldwide scale organizations, the International Organization for Standardization (ISO), the European Committee for Standardization (CEN) and the International Energy Agency (IEA) have complementary provided strategic and operational directions towards the implementation of energy efficiency improvements in buildings [11].

Finding proper techniques for a rational use of electrical energy has become, nowadays, even more important than the production of energy itself, because the Italian power grid is gradually becoming saturated and affected by many connection requests coming mostly from plants exploiting renewable energies. The present energy consumption which is necessary to the thermal comfort achievement of rooms and clean water represents almost 30% of the national energetic consumption and it is responsible for almost 25% of the national CO_2 emission, which is one of the principal cause of greenhouse effect and temperature heating

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[4].

An involvement is crucial to reach a new equilibrium, in harmony with the environment and respectful of future generation's rights. According to the latest Italian Energy Strategy Plan, a change in terms of energetic consumption and rational use of energy is necessary and is considered crucial in order to pursue sustainable economic growth.

The conventional measures that can be employed to improve energy performance in buildings can be classified into those that immediately relate to the building envelope i.e., the constructional elements, and those relating to the operation of energy systems used for heating, cooling, ventilation, hot water supply, etc.[12]. Apart from "conventional" measures, energy management techniques combined with innovative environmental technologies and advanced materials and systems may, if properly applied, affect drastically the process of saving energy in the building sector. A critical aspect in the design but also in the operational phase of a building, when renovation or retrofit actions are needed, is the evaluation and adjustment of the alternative measures based on a set of criteria such as energy consumption, environmental performance, investment cost, operational cost and indoor environment quality, security, social factors, etc. [12]. In some cases, the aforementioned criteria are in contrast or interrelate in a non-linear way, making the problem of reaching a globally optimal solution generally infeasible; researching for such optimal solution is usually attempted via two main approaches.

So it is clear that in order to reduce the consumption of electricity, it is necessary to change the consumption of buildings. The solutions can therefore be two:

- Envelope and plants retrofitting, which leads to a scenario of high savings at the cost of high investments and therefore to a long payback period;
- Automation and intelligence through smart buildings, which leads to medium savings with low investment hence short payback period.

In fact, with more than 10 buildings the payback period is around 3 years, which

https://doi.org/10.1016/j.enbuild.2020.109963

is lower than the payback period of retrofitting solutions which is around 15-20 years.

Therefore, monitoring the energy consumed in buildings, especially public buildings, is critical in order to reduce the consumption. In a smart building it is possible to control heating, ventilation, air conditioning, lighting, presence, security and other systems. With sensors, actuators and microchips, it is possible to collect and manage data according to a business' functions and services. Thanks to appropriate optimization, control and diagnostics algorithms,it is possible to minimize the environmental impact of buildings.

In the scientific literature various studies are presented regarding the optimization methodologies for the energy management of buildings. In accordance with the European Directive on building performance (EPBD) 2010/31 / EU [13], the next target, starting from 2021, will be the diffusion of almost zero energy buildings. The EU Delegated Regulation 244/2012 [14] establishes that an intermediate step towards this final goal is the so-called "cost optimization" where the level of energy efficiency guaranteed is optimal in terms of costs. There are numerous methods for the energy optimization, as GAs is the most popular, mainly because they do not usually converge to local minima and allow to explore large domains of solutions with a feasible computational burden while using single or multi-objective approaches (i.e. with two or more contrasting functions be optimized) [15] [16]. In the case of multi-objective functions, the optimization is implemented through the use of the pareto front [17]. The selection of the optimal solution on the pareto front is indicated by balancing the will and needs of the parties concerned, respecting the weights given to the different objective functions. Multi-objective approaches are very suitable for solving this problem, but this case study preferred to use a single-lens approach in order to compare the two different algorithms used(NSGA-II and Surrogate method).

This article describes a possible strategy of optimization with the surrogate method suitable for smart buildings, which was compared the NSGA-II optimization algorithm. Both focused on the energy consumption reduction and

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Figure 1: Case study: Smart Building at ENEA, building F40

minimization of unhappy residents percentage due to thermal discomfort. This percentage was determined by PMV index (Predicted Mean Vote) and PPD index (Predicted Percentage of Dissatisfied) [5] in the current regulation UNI EN ISO 7730:2006.

2. Description

A real office building located at ENEA (Casaccia Research Centre, Rome, Italy) was examined as a case study (Figure1). The building has an L-shaped structure, it is oriented 15° north-east and it was built between 1970 and 1972 and it is formed by three floors and a heating plant in the basement. There are 41 offices of different size with a floor area ranging from 14 to 36 m^2, 2 EDP rooms of about 20 m^2 each, 4 Laboratories, 1 Control Room and 2 Meeting Rooms, for a total of 1277,3 m^2. Each office room has from one up to two occupants. Each room and laboratory is equipped with fan-coils with on-off fan speed which is controlled by a room thermostat with hysteresis. The heating plant is a traditional natural gas boiler. The building is equipped with an advanced monitoring system aimed at collecting data revealing both external and internal conditions, electrical and thermal energy consumption. In order to simulate the variables of interest, a MATLAB Simulink simulator based on

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HAMBASE [5, 6] model was developed. The control variables are:

- Zone set point which can be set using thermostats in each room;
- Flow set point which can be set by means of special instrumentation in the building's thermal power plant.

In fact, the variables that can be set in the simulator are actually modifiable in the modeled building. Simulink was used to both model the described building, together with all its thermal and electrical components and simulate the behavior of the F40 building was used the HAMBASE software, which exploited the internal temperature model, the relative humidity of the indoor air and the energy consumption required for the heating and cooling of a multi-zone building. The purpose of the software developed is to simulate the energy saving strategies and control logics in order to maximize energy savings, and therefore to minimize the cost. The outputs are:

- environmental comfort;
- euros.

The following section will describe the simulator, but for more details regarding the different specifications of the simulator,the reader can refer to other more detailed articles [7].

2.1. Description of simulator

Simulink is the software chosen to model the building and all its thermal and electrical components (heating system, fan coil power supply network, lighting network). Simulink is a software dedicated to modeling, simulation, and analysis of dynamic systems, which is closely integrated with MATLAB. On the other hand, HAMBASE (Heat, Air and Moisture model for building and system evaluation) purposely helped to simulate the behavior of the F40 building. The HAMBASE software uses the model of the internal temperature, relative humidity of the internal air, and energy consumption required for the heating

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and cooling of a multi-zone building. The purpose of the software developed is to allow to simulate energy saving strategies and control logic, having as output of the simulation itself two main parameters such as:

- Internal environmental parameters, such as internal temperature and relative humidity that identify the environmental comfort;
- Aggregate parameters such as electricity and methane consumption that identify the energy expenditure,calculated in terms of euro spent.

The parameters received as input from the simulator are different, the most significant for the purposes of calculating the two functions PPD and euro are flow set point and zone temperature set point. These two decision-making variables certainly can determine the value of the total objective function, however, they are not the only ones that have a direct influence on the value of the objective function. Indeed, there are other parameters that affecting the function, but they are not set dynamically. These parameters are mainly six: the national unit price curve (PUN) that determines the dynamism of the energy price; the external climatic conditions that affect the trend of consumption and the climatic conditions inside the building; the external and internal humidity; energy parameters to best simulate the energy absorption of the building; the activities and occupation of the different areas and rooms of the building; and other parameters. In output, a multiplicity of values regarding the thermal conditions and consumption of the building is obtained, but for what concerns the use of the simulator in this case, it will stop to specify only the output values of the PPD (Predicted Percent Dissatisfied) and the cost (€), calculated respectively by the two subsystems of the simulator Subsystem Comfort Meter and Subsystem Dynamic Pricing highlighted in Figure 2. In fact in the following figure we can see an idea of the general scheme of the simulator and in particular a zoom on the two subsystem that will be described in detail in the next sections.

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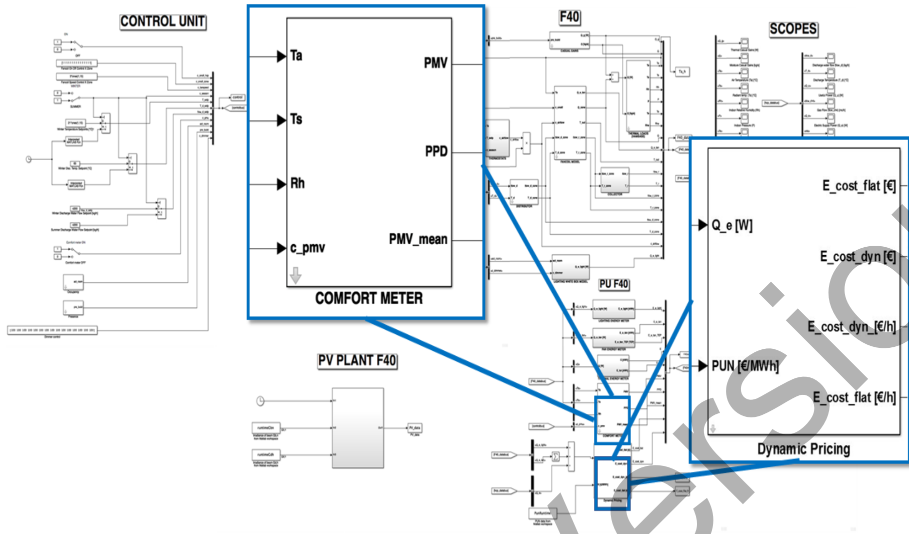

Figure 2: General scheme of the simulator

2.1.1. Subsystem Comfort Meter

The thermo-hygrometric comfort indices given back by the simulator are in line with the UNI EN ISO 7730:2006 standard, which specifies the methods for predicting the overall thermal sensation and the degree of discomfort (thermal dissatisfaction) of people. The Danish scholar Fanger established two equations described in detail in UNI EN ISO 7730:2006 for the evaluation of thermo-hygrometric well-being. PMV expresses the level of satisfaction of a large sample of people working in the same building and expressing their thermal sensation through a psychophysical scale (Figure 3). In the following Figure 3 it is possible to see the ranges of possible values that the PMV index can accept, if the thermal enviroment is neutral the values will be 0, but if the people are warm or cold the value will be respectively positive or negative. The PPD can be computed using PMV model, in fact they are experimentally related through the following formula:

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PMV	Thermal environment evaluation
+3	very hot
+2	hot
+1	slightly hot
0	neutral
-1	fresh
-2	cold
-3	very cold

Figure 3: PMV and evaluation of the thermal environment

$$PPD = 100 - 95 * e^{-(0{,}03353*PVM^4+0{,}2179*PVM^2)} \tag{1}$$

It should be noted that it is not possible to use PMV and PPD evaluation indices in all working conditions but only when certain parameters are included in the following ranges (Figure 4). Figure 4 reports the ranges through which it is possible to apply the PMV and PPD indices,in terms of energy metabolism, thermal insulation of clothing present and the air temperature and velocity.

Energy metabolism	Between 46 and 232 [W/m2]
Thermal insulation of clothing	Between 0 and 0,310 [m2 °C/W]
Air temperature	Between 10 and 30 [°C]
Air velocity	Between 0 and 1 [m/s]

Figure 4: Limits of applicability of the PMV-PPD criterion

Among the variables characterizing the building model, there are four variables that were set to their typical values. These variables are: metabolism (70 [W/m^2]), external work (0 [W/m^2]), clothing (1 [0.18^{o}C]), and air velocity (0.1 [m/s]). The convergence (Figure 2) of four input channels was performed during

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the modelling of this subsystem. These channels are:

- Ta = air temperature [°C], simply the temperature perceived inside the room;
- Ts = radiant temperature [°C], i.e. the temperature of the walls inside the room, including the ceiling and floor;
- Rh = relative humidity inside;
- c_pmv = comfort meter.

When appropriately processed with a function that takes into account both the inputs and the limits of applicability of the criterion, these channels produce three different output channels in output, which, however, can only be traced back to the PPD:

- PMV = expected average score (for each zone);
- PMV_mean = average expected average score (average of values for each zone);
- PPD = expected percentage of dissatisfaction [%].

2.1.2. Subsystem Dynamic Pricing

The Subsystem relative to the simulation of the cost of the consumed energy is modelled as in Figure 2 where two inputs can be examined:

- Q_e_tot= total electric power consumed[W], which is calculated as the sum of fan-coil ventilation consumption, lighting consumption and heat pump consumption (electric power supplied)

$$Q\_e\_tot = Q\_e\_fan + Q\_e\_light + Q\_e \tag{2}$$

- PUN = single national electricity price [€/MWh], i.e. the reference price of electricity on the Italian electricity exchange (IPEX, Italian Power Exchange);

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and 4 outputs properly calculated as:

- E_cost_flat = cost of energy consumed with static price [€];
- E_cost_flat_h = cost of energy consumed with static price sampled hour by hour [€/h];
- E_cost_dyn = cost of energy consumed with dynamic price [€];
- E_cost_dyn_h = cost of energy consumed with dynamic price sampled from hour to hour [€/h].

By looking at the inputs and outputs of this subsystem, it is possible to identify the consequences, since the multiplications between the amount of energy consumed[W] and its cost [€] ordered the variables in terms of magnitude and measure. The attention was drawn by the values of dynamic cost, in particular those sampled from hour to hour.

2.2. Description of problem

The optimization problem is the minimization of the cost while maintaining adequate comfort level inside the buildings. The problem analyzed is a multi-objective problem considering the cost and the PPD.

$$min_{(x_1,x_2)}\{E\_cost\_dyn\_h + PDD/12\} \tag{3}$$

The constraints of the problem are the following:

- $21 \leq x_1 \leq 25$
- $8 \leq x_2 \leq 12$

Where:

- x_1 is the zone set-point. It is a vector of 24 elements (one for each our of the day). It can change from 22 to 25 Celsius degree;
- x_2 is the flow set-point. It is a vector of 24 elements (one for each our of the day). It can change from 8 to 12 Celsius degree ;

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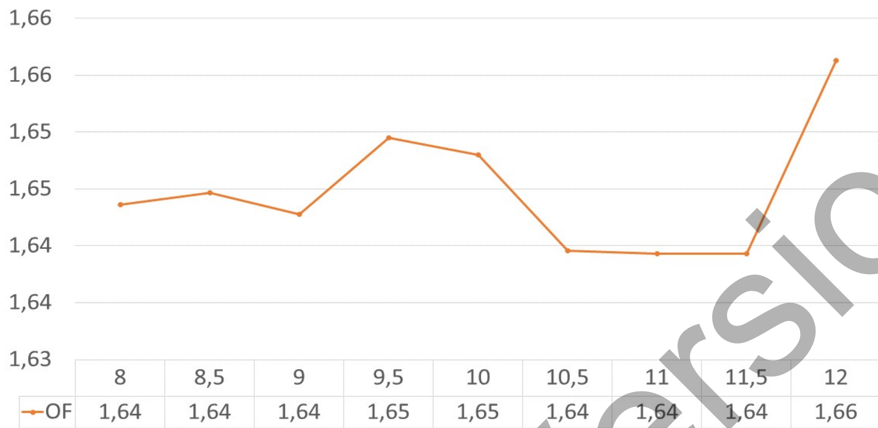

Figure 5: Trend of objective function when $X1$ is equal to 23

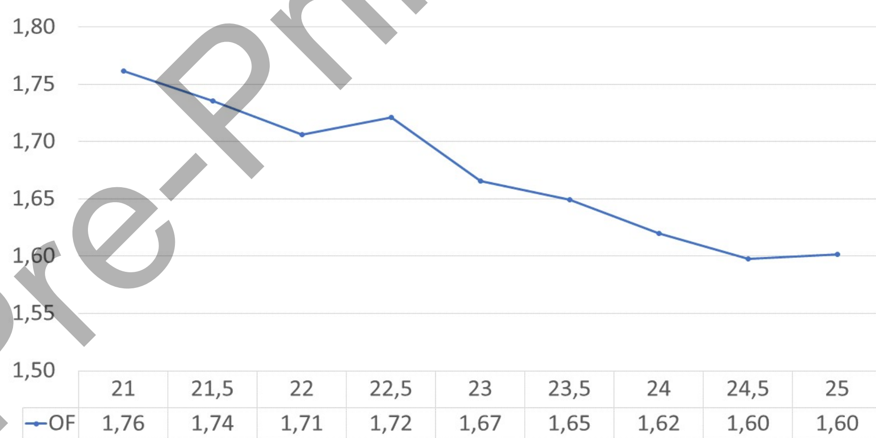

Figure 6: Trend of objective function when $X2$ is equal to 10

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The analysis of the objective function was carried out while changing one decision variable at a time (zone set-point and flow set-point), setting it progressively to each single value assumable, respecting the constraints of the problem and define the baseline to calculate the efficiency of optimization systems.

The behaviour of the objective function is reported in Figure 5 and 6, varying $x2$ and $x1$ respectively. The trend of the objective function both compared to $X1$ and $X2$ has several local minima, this highlights the complexity of the problem and the difficulty to find global optimum. Each simulation is about a single day in which it is possible to set the different set-points from hour to hour. This made the system dynamic and efficient in the vision of a hypothetical functioning in reality. The simulator processes,as input data, both the values of the set up decision variables and the final states of the simulator returned by the optimization system.

3. The genetic method for smart building

The NSGA-II is a genetic algorithm proposed by Kalyanmoy Deb in 2000 and represents an advanced revision of the NSGA, Deb himself, dating from 1994. This algorithm is part of the family of elite evolutionary algorithms, which is distinguishes from non-elitarians by passing from one generation to the next without lost good solutions. The abbreviation NSGA (Non dominated Sorting Genetic Algorithm) emphasizes how solutions for the optimization problem are ordered in accordance with the concept of non-dominance.

NSGA-II provides that all solutions of a population are classified according to a dominance order. Non-dominated population solutions will have rank 1. Solutions that are not dominated by the entire population, except for those with rank 1, will have rank 2 and so on. The computational complexity of this procedure is the sum of the complexities required to identify each non-dominated set. It is important to notice that once the first non-dominated set is identified, the number of remaining solutions will be smaller than the original number of individuals in the population, hence the classifications after

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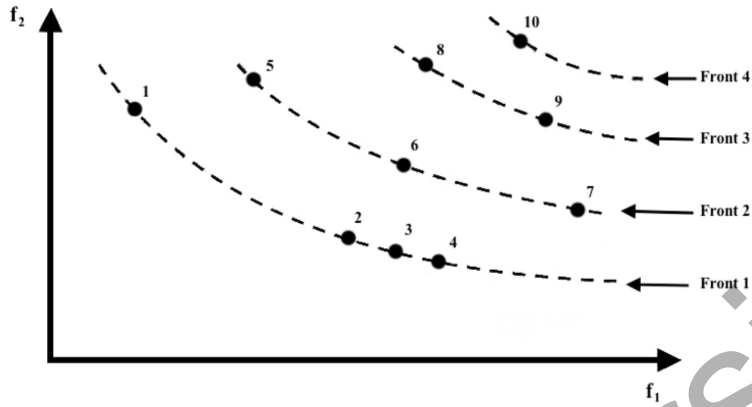

Figure 7: Example of sorting by rank with population to 10 individuals

the first one will require less computational complexity. The entire classification process has $O(MN2)$ complexity, with M number of targets and N size of population. Figure 7 shows an example of ordering by levels, of a population of 10 individuals, in a problem of minimization of two target functions. Assigning a rank to all solutions means the the crowded distance is assigned, which is a value that indicates how much a solution is isolated. The aim is to preserve the diversity of solutions on the same non-dominated front, thus maintaining a good distribution. They are ordered iteratively in a worsening order with respect to each target function. Extreme results with the best and worst fitness are assigned at an infinite crowding distance. The others were assigned with a value proportional to the distance between the i-solution and the previous and subsequent solutions.

When comparing two solutions the rank is compared first, if they have the same rank the crowding distance is compared. It is possible to notice how the steps that the NSGA-II performs are the same as those of any genetic algorithm:

Steps of the Genetic Method (NSGA-II) GM

1 Population initialization;

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2 Rank assignment and crowding distance;

3 Application genetic operators

4 A union of father and daughter generation;

5 Rank assignment and crowding distance;

6 Selection of the best;

7 Return to step 3 until the stop condition is met.

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4. The surrogate method for smart building

The Surrogate Method solves the optimization problem by using the gradient method. This procedure presents an iterative structure that, in each cycle, transforms the original problem with discrete decision variables, into an optimization problem with continuous decision variables. The last problem is known as Surrogate. Subsequently, the gradient estimate, which allows to update the solution, is performed in the discrete field. The transition from the discrete problem to the continuous problem occurs at each cycle of the algorithm and the update of the surrogate solution is obtained through the variation of the objective function computed in the discrete state.

The Surrogate Method gives good results in various application areas, such as the lot sizing problems or the urban traffic, failing to find the solution good/sub-optimal original discrete problem and reaching the very fast convergence [1], [2], [3].

The steps sequence of the algorithm is reported in Figure 1.

Vector $Z = (X_1, X_2)$ is an $2N$-dimensional decision vector (N is equal to 24 where each component denotes the degree for zone flow set-point for each hour of the day, subject to the capacity constraints A_d and $J_d(Z)$ is the cost incurred when the state is Z. The integer capacity constraint is relaxed and a resulting surrogate problem is obtained.

The basic idea of this method is to solve a continuous optimization problem by stochastic approximation methods and establish the fact that when (and if) a solution of the relaxed problem ρ^* is obtained it can be mapped into a discrete point $z = f(\rho^*) \in A_d$ which is in fact the solution of our problem.

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Note however, that the sequence $\{\rho_k\}$, $k = 1, 2, \ldots$ generated by an iterative scheme for solving the relaxed problem consists of real-valued solutions which are unfeasible, since the actual system involves only discrete resources. Thus, a key feature of the Surrogate algorithm is that at every step k of the iteration scheme, the discrete state is updated through $z_k = f_k(\rho_k)$ as ρ_k is updated. This has two advantages:

- the cost of the original system is continuously adjusted (in contrast to an adjustment that would only be possible at the end of the Surrogate optimization process);
- it gives the possibility to make use of information typically employed to obtain cost sensitivities from the *actual* operating system at every step of the process.

Note that there is an additional operation: the $\{z_k\}$ corresponds to feasible states based on which one can evaluate estimates $\nabla L_c(\rho_k)$, calculated on actual system z_k (not the surrogate state ρ_k, see step 3 of Fig. 1). We can therefore see that this scheme is intended to combine the advantages of stochastic approximation type of algorithm with the ability to obtain sensitivity estimates with respect to discrete decision variables.

Figure 8 shows how the optimizer works, focusing on the interaction between the surrogate method and the simulator.

5. Results analysis

Each simulation is about a single day in which it is possible to set the different set-points every hour. This made the system dynamic and efficient in the vision of a hypothetical functioning in reality.

The simulator takes in input both the values of the decision variables that were set up and the final states of the simulator returned by the optimization system. The goal of the problem is to minimize a multi objective function with cost and comfort (euro [e] and PPD [%]). To evaluate the efficiency of the algorithm, the combination of set-points with which the F40 building is currently air-conditioned during the summer season was taken into consideration:

- Zone $set\_point = 22^\circ C$;
- Flow $set\_point = 10^\circ C$;

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Algorithm 1 The Surrogate Method

1: Initialize $\rho_0 = z_0$ satisfying the constraints ▷ ρ_0 is a continuous vector, z_0 is a discrete vector,
▷ both of dimension $M + 1$
2: Initialize $\rho^* = \rho_0$, $z^* = z_0$ ▷ ρ^* is the optimal solution of the continuous problem
3: Initialize $h = 0$
4: **while** $((k \leq K) \vee (h \leq H))$ **do** ▷ K and H integer parameters
▷ **Form the selection set** $S(\rho_k)$ (steps 5-13):
▷ $S(\rho_k)$ is a set of discrete vectors
5: Initialize I= $\{1, ..., M\}$ and $v = \rho$ - $\lfloor \rho \rfloor$ ▷ I is the set of M integers, v is a continuous vector
▷ the component $v[i]$ is the decimal part of the $\rho[i]$ component
6: **while** $I \neq \emptyset$ **do**
7: $i = \arg\min_{j \in I} (v[j])$
8: $y[i] = v[i]$
9: $W_i = \sum_{j \in I} e_j$ ▷ W_i integer vector, e_j the versor with j-th component equal to 1
10: $v = v - y[i]W_i$
11: $I = I \backslash \{i\}$
12: **end while**
13: $S(\rho_k) = \{W_i - \lfloor \rho \rfloor, i = 0, .., M\}$
▷ **Transform the continuous problem to the discrete problem**
▷ D is the set of the discrete vectors that satisfy the constraints
14: $z_k = f(\rho_k) = \arg\min_{d \in D} \|d - \rho_k\|$ ▷ Transformation function f
▷ **Gradient estimate**
15: $\nabla OF(\rho_k) = [\nabla_1 OF, ..., \nabla_M OF]^T$ ▷ OF Objective function declared in (3),
▷ where $\nabla_j OF(\rho_k) = OF(p) - OF(q)$
▷ where k satisfies $p - q = e_j$ and $p, q \in S(\rho_k)$,
▷ **Update state**
16: $\rho_{k+1} = f[\rho_k - \eta_k \nabla OF(\rho_k)]$. ▷ η_k is the step size of the gradient method
▷ **Optimal solution update**
17: **if** $OF(\rho_k) \leq OF(\rho^*)$ **then**
18: $\rho^* = \rho_k$
19: $h = 0$
20: **else**
21: $h = h + 1$
22: **end if**
23: **end while**
▷ **Return the optimal solution** z^*
24: **Return** $z^* = \arg\min_{z_k} OF(z_k)$.

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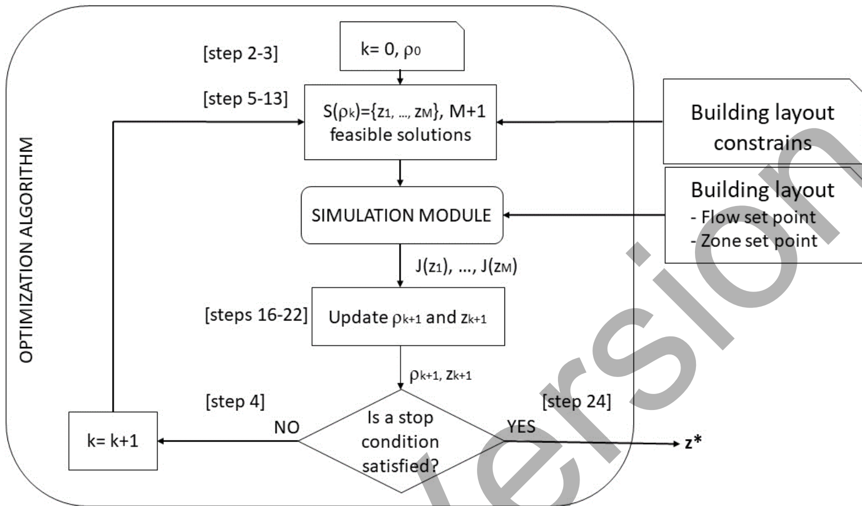

Figure 8: General scheme of the proposed approach

which were kept constant throughout the simulation period. The simulations were performed by taking three different initial internal temperatures: $T^0 = 21; 23; 25[^{\circ}C]$.

It is possible to observe the results obtained by simulating the real functioning of the building, without any kind of optimization (RC Real Case, with static set-point), in comparison with the optimized one, in which each simulation involved changing the flow set-point and the zone set-point in specific ranges. In table 1 and table 2 a comparison between Real Case (RC), Surrogate Method (SM) and genetic algorithm ($NSGA-2$) is reported, considering the average trend in a day. In particular in table 1 the values of the average objective function are reported, for the three different initial temperatures. On the other hand, in table2 reports the average improvement given by the optimization methods. The best performances are given by the Surrogate Method when the initial temperature is equal to 23°.

In Fig.9, Fig.10, Fig.11 the trend of the objective function for the two optimization methods is shown during the 24-hours. The biggest gap occurs in the early hours of the afternoon when the Surrogate Method provides better performances. When the initial temperature is equal to 25° the trend of the optimization methods is different

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Table 1: Average results

Initial temperature	RC		SM		NSGA-2	
	E$_{COST}$ (¬)	PPD (%)	E$_{COST}$	PPD	E$_{COST}$	PPD
21°C	22.74	6.17	20.4	7	20.64	7.1
23°C	29.84	6.74	21.36	8.27	23.52	8.25
25°C	36.84	10.82	30	11.9	32.64	10.9

Table 2: Objective function

Initial temperature	RC		SM		NSGA-2	
	OF (¬)	Saving (%)	OF	Saving	OF	Saving
21°C	1.46	-	1.44	10.4	1.45	9.2
23°C	1.8	-	1.58	28.3	1.67	21.2
25°C	2.44	-	2.23	18.6	2.28	11.4

because it is more difficult to satisfy users when the initial temperature is higher.

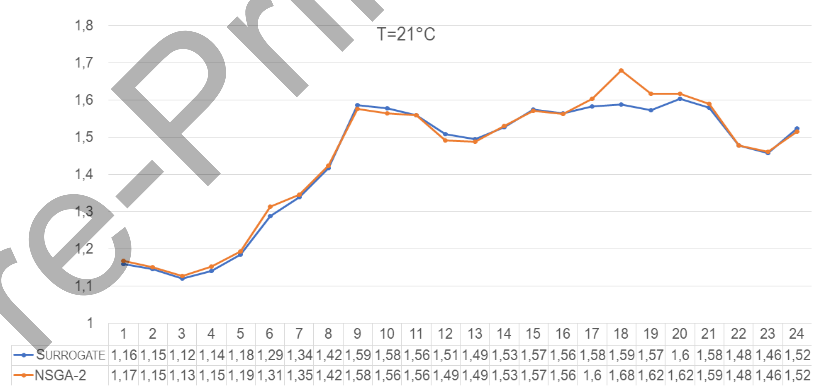

Figure 9: Trend of objective function when $T^0 = 21$

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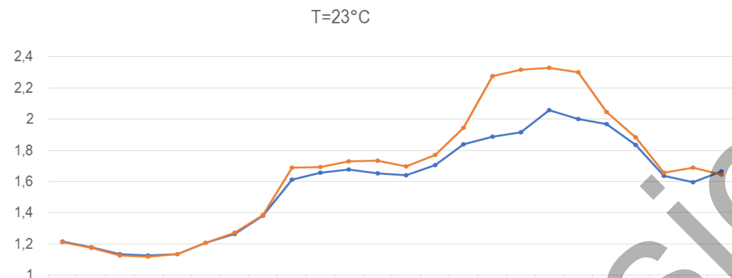
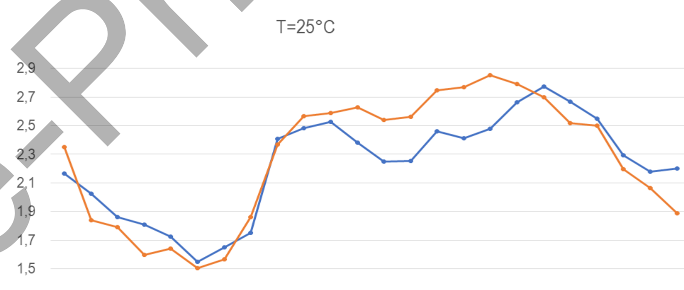


	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
SURROGATE	1,22	1,18	1,14	1,12	1,13	1,21	1,26	1,38	1,61	1,66	1,68	1,65	1,64	1,71	1,84	1,89	1,91	2,06	2	1,97	1,84	1,63	1,6	1,67
NSGA-2	1,21	1,18	1,13	1,12	1,14	1,21	1,27	1,38	1,69	1,69	1,73	1,73	1,7	1,77	1,94	2,28	2,32	2,33	2,3	2,04	1,88	1,66	1,69	1,65

Figure 10: Trend of objective function when $T^0 = 23$



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
SURROGATE	2,2	2	1,9	1,8	1,7	1,5	1,7	1,8	2,4	2,5	2,5	2,4	2,2	2,3	2,5	2,4	2,5	2,7	2,8	2,7	2,5	2,3	2,2	2,2
NSGA-2	2,3	1,8	1,8	1,6	1,6	1,5	1,6	1,9	2,4	2,6	2,6	2,6	2,5	2,6	2,7	2,8	2,9	2,8	2,7	2,5	2,5	2,2	2,1	1,9

Figure 11: Trend of objective function when $T^0 = 25$

https://doi.org/10.1016/j.enbuild.2020.109963

6. Conclusion

Through this study it was possible to identify and understand two different optimization strategies applied smart buildings, which aim to reduce energy consumption and, at the same time, minimize the percentage of unsatisfied occupants caused by thermal discomfort. Furthermore, this combination of simulator and optimizer will be used for experiments in the field of local energy communities, which is one of the last topics of the system research of the ENEA Research Center, whose goal is to achieve autonomy, sustainability and efficiency with respect to today's energy needs.

On average, a theoretical saving of 16.5% was found compared to the reference case, in particular the two algorithms, NSGA-II and Surrogate Method, brought respectively an average theoretical saving of 13.9% and 19.1%, even though it would be more correct and consistent to consider and analyze the three cases separately. As a matter of fact, for the first two cases it was examined the Surrogate Method is more efficient, obtaining much better results, while in the last case (T^0=25°C) the NSGA-II algorithm is competitive in finding an excellent solution during the first hours of the simulation, even though Surrogate Method is once again the most efficient throughout the day. It is here used the term theoretical savings because the strategy was not applied to the actual building. In this regard, it is appropriate to make some considerations to have a better understanding of the differences that may arise in dealing with a problem of this type compared to the case simulated:

- The results obtained are the result of simulations which, although accurate, do not reproduce the exact behaviour of the F40 building;
- The external climatic conditions, taken as input from the simulator, are not the result of a forecast but are a record of the conditions revealed in 2013 season. This implies the need of extremely accurate weather forecasts;
- The trend of the PUN, taken as an input from the simulator, represents energy prices dating back to 2013 in the same period of the simulation;
- The PPD index used to evaluate the percentage of dissatisfied personnel, although imposed by the regulations, is a subjective index and difficult to calculate in reality since it depends on parameters such as metabolism and clothing, specific to each individual;

https://doi.org/10.1016/j.enbuild.2020.109963

In conclusion it can be stated that the two algorithms have both led to economic savings without losing sight of PPD and that however a different and innovative approach as that of the Surrogate Method gave the possibility to obtain better results than a classic approach such as that with NSGA-II. Right this way, we are already working to perform the integration with the optimizer will be upgraded so that the different values of the zone set-points of the 15 different climate zones of the building can be managed individually. In addition, we are working on a new version of the simulator that integrates the PV (PhotoVoltaic) and a storage for an even more effective management of energy consumption. Finally, to validate the solutions proposed in a real case, this strategy will be applied to the F40 smart building.

https://doi.org/10.1016/j.enbuild.2020.109963

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