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Two-Stage Multi-Objective Meta-Heuristics for Environmental and Cost-Optimal Energy Refurbishment at District Level

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Abstract: Energy efficiency and environmental performance optimization at the district level are following an upward trend mostly triggered by minimizing the Global Warming Potential (GWP) to 20% by 2020 and 40% by 2030 settled by the European Union (EU) compared with 1990 levels. This paper advances over the state of the art by proposing two novel multi-objective algorithms, named Non-dominated Sorting Genetic Algorithm (NSGA-II) and Multi-Objective Harmony Search (MOHS), aimed at achieving cost-effective energy refurbishment scenarios and allowing at district level the decision-making procedure. This challenge is not trivial since the optimisation process must provide feasible solutions for a simultaneous environmental and economic assessment at district scale taking into consideration highly demanding real-based constraints regarding district and buildings' specific requirements. Consequently, in this paper, a two-stage optimization methodology is proposed in order to reduce the energy demand and fossil fuel consumption with an affordable investment cost at building level and minimize the total payback time while minimizing the GWP at district level. Aimed at demonstrating the effectiveness of the proposed two-stage multi-objective approaches, this work presents simulation results at two real district case studies in Donostia-San Sebastian (Spain) for which up to a 30% of reduction of GWP at district level is obtained for a Payback Time (PT) of 2–3 years.

Keywords: energy; environmental; global warming potential; district refurbishment; multi-objective; optimization

1. Introduction

The building sector is one of the highest energy consumers and, hence, one of the major sources of environmental impacts worldwide [1]. In order to reduce climate change effects and move towards a low carbon economy, the European Union (EU) has settled Global Warming Potential (GWP) reduction targets [2]. For assuring the success in this energy transition process, municipalities have to be necessarily involved and, therefore, the application of energy performance measures [3] at building and district scale has become a relevant aspect to be considered nowadays [4–7].

Despite the efforts undertaken by municipalities for achieving GWP reduction objectives, connection between targets at city level and the possibility of implementing specific measures at building and district level remains an outstanding issue. More specifically, actions proposed at city scale often disregard available budget or building architectural constraints. In line with it, several

European projects [8–13] focused on decision support tools for yielding to an energy-efficient design of buildings, cities and districts have recently been funded.

Due to the intrinsic characteristics of the environmental and optimal energy refurbishment problems, most of the recent related works in this research area are based on multi-objective optimization algorithms [14–21]. These algorithms commonly optimise several metrics (that often pursue conflicting goals) while meeting the constraints of the problem at hand and achieving a large number of non-dominated solutions approximating the Pareto front. Following this multi-criterium optimization idea, the authors in [22] propose a retrofitting use case with the aim at minimizing the energy consumption, the CO_2 emissions and the overall costs while maximizing the thermal comfort in a public school. The proposed solution is based on an evolutionary multi-objective optimization algorithm (NSGA-III). Within the same line of research, several optimization problems involving building design are tackled in [23,24]. These works present diverse population-based meta-heuristic algorithms that range from the NSGA-II and the Pareto-Archived Evolution Strategy (PAES) to the Particle Swarm Optimization (PSO). In [25], a hybrid optimization algorithm that selects the retrofit actions to apply, such as: the window types, the external wall insulation materials, the roof insulation materials, and solar collectors, is presented aiming at increasing the building energy savings and decreasing energy consumption and retrofit cost. Moreover, authors in [26] use a Genetic Algorithm (GA) merged with a dynamic simulation tool to investigate the best retrofit opportunities and, hence, optimise the energy savings, the overall cost and the indoor thermal comfort. In addition, the work in [27] presents different optimization methods at building design level based on a multi-objective GA. The novelty of this work lies in modifying the behavior of the conventional GA by introducing adaptive operators and also changing the meta-model approach so as to enhance the convergence and speed of the algorithm.

In related literature, most retrofitting planning problems tackled with meta-heuristic algorithms generate optimal solutions that meet highly demanding real-based requirements along the iterative process. Moreover, at each generation, the procedure usually entails a great number of energy calculations, which leads to overall time heightening. To overcome this issue, several works in the literature are focused on alleviating the iterative process and enhancing the convergence of the algorithms. Specifically, an optimal tuning of the algorithm's parameters and a hybrid meta-heuristic algorithm combined with a local search is presented in [28,29], respectively. In light of the computational complexity that arises from the additional energy simulations required in this type of problems, an optimization process for tuning parameters may be impractical. In order to address this concern, an alternative approach based on hybrid optimization algorithms is presented in [30,31], where the main objective is to restrain the search space in order to alleviate the complexity of the problem, and then apply gradient-based local search algorithms for boosting the convergence towards the optimal region.

Regarding optimization approaches for energy retrofitting at district scale, there is no much related work in the literature. However, authors in [32] propose a multi-objective GA for assessing cost-optimality in hospitals built in Italy between 1991 and 2005. In this proposal, domestic hot water based on the installation of an efficient gas boiler is considered as a feasible energy retrofitting measure. Similarly, in [33], a tool named RESCOM (Residential Energy System Concept design stage Optimization Model) is provided as an optimal framework for efficiently solving retrofitting problems at urban scale.

In this regard, there is no much research focused on deriving an approach in which the optimization is jointly performed at building and district level. Therefore, the proposed two-stage methodology, in which the multi-objective algorithms are specially designed ad hoc for the energy retrofitting problem by means of considering different fitness functions at each stage, clearly represents a novelty and an advance towards the state of the art in this field. Specifically, the presented approach proposes two novel multi-objective meta-heuristics based on the Non-Dominated Sorting Genetic Algorithm (NSGA-II) and on the Multi-Objective Harmony Search algorithm (MOHS) specially tailored for obtaining optimal refurbishment solutions at building and district scale. As mentioned above, the paper proposes two different two-stage approaches based on the multi-objective algorithms NSGA-II and MOHS in order to provide: (1) Stage 1: *Building level optimization* that maximizes the reduction of Energy Consumption (R_{EC}) while minimizing the Investment Cost (IC); (2) Stage 2: *District level optimization* aimed at maximizing the GWP reduction (R_{GWP}) while minimizing the total Payback Time (PT). The proposed work assesses the most common energy retrofitting approaches in terms of passive, renewable and active strategies (see Section 2 for more details) and has been successfully applied to two real-based case studies in Donostia-San Sebastian (Spain). First, a basic use case of the district of Gros; and, second, a simple and an advanced use case in the historical city center. For both case studies, optimal refurbishment strategies per building category are presented along with an extensive assessment of multi-objective performance indicators for NSGA-II and MOHS, such as: Hypervolume, Coverage Rate, among others. Finally, the selection of the optimal scenario at district level is provided per case study based on the targets defined by Donostia-San Sebastian for 2030 in terms of GWP reduction.

The paper is organized as follows: Section 2 establishes the formulation of the district energy retrofitting problem, whereas Section 3 and subsections therein provide details on the considered multi-objective heuristics. Section 4 describes the considered case studies in Donostia-San Sebastian and Sections 5 and 6 discuss the simulation results obtained by using the aforementioned heuristics at building and district level. Finally, Section 7 ends the manuscript by presenting the conclusions of the work and by outlining future research lines.

2. District Energy Retrofitting Problem

As stated in Section 1, this paper proposes two multi-objective meta-heuristic approaches that cost-effectively optimize the environmental and energy refurbishment of districts considering a set of certain pre-established constraints at building level.

Despite the fact that nowadays there are diverse energy refurbishment strategies, this work assesses some of these strategies, which are divided into three main groups. The first group refers to some passive strategies or energy conservation measures, the main objective of which is to reduce the energy demand of the building. The second group is composed of renewable strategies, the main objective of which is to generate energy onsite or offsite of the building by renewable sources. Finally, the third group contains some active strategies, which aim at reducing the energy consumption of the building.

Passive strategies are designed to provide a significant reduction of the energy need for heating and cooling, independently of the energy and of the equipment that will be chosen to heat or cool the building. These strategies are mainly based on the increment of the thermal resistance of the envelope, on the replacement of the current windows, on the reduction of air leakage or on the usage of bioclimatic strategies, are aimed at improving the life quality of inhabitants reducing the energy demand, reducing the economic bill, increasing the indoor air temperature in winter, reducing the indoor air temperature in summer and increasing the thermal comfort of the inhabitants. According to the location of the strategies related to the improvement of the thermal resistance of the envelope, there are three main groups: external wall, internal wall and air chamber insulation strategies. The refurbishment strategies of insulation of the external wall consist of acting from the outside of the existing wall, placing a new skin that allows for improving the thermal performance of the wall. Mainly, there are two systems for these types of actions: external thermal insulation systems and ventilated facades. For this study, the application of the ventilated façade is considered, which is a coating system of the building walls which leaves a ventilated chamber between the coating and the insulation. With this system, a continuous insulation can be achieved for the exterior of the building, protection of the internal sheet as well as the slab edges. Internal wall insulation involves the application of insulation to the interior face of external walls in order to improve the thermal performance of the property. Internal wall insulation can, however, be disruptive and requires the removal and re-fixing of items such as switches, radiators and kitchen units. There are several main methods of installation. For this work, the method where a semi-rigid wool batten is placed against the wall is selected. Appropriately spaced battens are placed on top and screws driven through the batten, through the insulation and into the wall. Rigid or semi-rigid insulation can then be installed between the battens with plasterboard then installed. Finally, in the case of the existence of air chambers in the thermal envelope of the building to retrofit, it is possible to fill these chambers with thermal insulation. The most common methods are the injection of polyurethane (PUR) foam and cellulose. Injected insulation reduces the thermal conductivity of the envelope. However, this strategy increases the influence of the existing thermal bridges. To conclude with these passive strategies, this work considers another relevant strategy, which improves the thermal properties of the current windows by substituting the frame and also the glazing.

With regard to the passive refurbishment strategies three efficiency levels—basic (B), efficient (E) and advanced (A)—are defined in order to outline the degree of energy efficiency improvement of buildings. Thus, different insulation thicknesses are proposed for the basic, efficient and advanced efficiency levels. The basic efficiency level (B) only considers the refurbishment strategies that suffice the minimum thermal requirements imposed by current Spanish regulations [34]. The efficient level (E) is based on refurbishing strategies that improve the thermal properties by 30% compared with current regulations. Finally, the advanced strategies (A) settle the building thermal parameters to higher values, resembling those used in the Passive House standard [35].

This being the case, the first option proposed (1) corresponds to investing in a *ventilated façade system* that consists of a layer of insulation, an aluminum substructure and a ceramic outlayer. The second strategy (2) proposes *indoor thermal improvement solutions* that entail a layer of insulation and plasterboard. The third refurbishment strategy (3) is an *air chamber insulation injection solution* composed of an insulation layer. Finally, the fourth refurbishment strategy (4) is focused on *replacing the windows* by substituting the frame and also the glazing. As previously introduced, each strategy has different efficiency levels, hence 11 different options (1B, 1E, 1A, 2B, 2E, 2A, 3B, 3E, 4B, 4E, 4A) are considered.

Referring to the first, second and third strategies, ventilated façade system, indoor thermal improvement and air chamber insulation solutions, different insulation thicknesses are proposed for basic (1B, 2B, 3B), efficient (1E, 2E, 3E) and advanced (1A, 2A) efficiency levels (see Table 1 for more details). Similarly, in relation to the energy efficiency levels of the windows replacement (4), different glazing options are defined for basic (4B), efficient (4E) and advanced (4A) types (Table 1). Finally, regarding the air chamber insulation strategy (3), this work does not considere the application of the advanced efficiency level (3A) due to the elevated thickness required for this level that cannot be implemented in the current Spanish buildings.

Table 1. Insulation thicknesses and Glazing parameters for the considered Passive Refurbishment Strategies (RS).

Refurbishment Strategies (RS)	Thicknesses (cm)		
	Deck	**Façade**	**First Floor Slab**
1B, 2B, 3B	8	5	6
1E, 2E, 3E	9	10	13
1A, 2A	15	25	30
	Glazing (W/(m^2 K)		
4B	Double glazing (2.7) & Aluminium frame (2.9)		
4E	Low-emissivity coated glazing (2.0) & Polyvinyl chloride (PVC) frame (2.0)		
4A	Low-emissivity coated glazing (1.4) & Wooden frame (1.2)		

The aforementioned strategies work towards energy conservation refurbishment, but this work also considers renewable energy sources (5) such as the *installation of a solar thermal system* (5S) or *installation of photovoltaic panels* (5P) on the roof of the building. The solar thermal system uses solar energy to heat the water in such a way that the electricity and natural gas usage of the installed water heaters is reduced. The photovoltaic panels (PV) aim at generating electricity and exporting it to the grid. Within this work, the self-consumption toll applicable in Spain for the electricity generated by PV panels has not been considered.

Finally, some new energy generation technologies (6) such as a biomass boiler with 87% of efficiency (6BI), a natural gas condensing boiler with 110% of efficiency (6N) and a water to air heat pump with cooling and heating COP of 3.27 and 3.1, respectively (6HP), are also taken into account.

As it can be easily seen, all the refurbishment strategies cannot be jointly applied. Table 2 depicts by means of a symmetric matrix representation the strategies that can be employed together (*1*) and those that cannot be combined (*0*). It is important to note that solar and photovoltaic panels strategies (5S, 5P) can be combined to cover up the total useful roof surface.

Table 2. Symmetric matrix for the total number of Refurbishment Strategies (RS).

RS	1B	1E	1A	2B	2E	2A	3B	3E	4B	4E	4A	5S	5P	6BI	6N	6HP
1B	1	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
1E	0	1	0	0	0	0	0	0	1	1	1	1	1	1	1	1
1A	0	0	1	0	0	0	0	0	1	1	1	1	1	1	1	1
2B	0	0	0	1	0	0	0	0	1	1	1	1	1	1	1	1
2E	0	0	0	0	1	0	0	0	1	1	1	1	1	1	1	1
2A	0	0	0	0	0	1	0	0	1	1	1	1	1	1	1	1
3B	0	0	0	0	0	0	1	0	1	1	1	1	1	1	1	1
3E	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1
4B	1	1	1	1	1	1	1	1	1	0	0	1	1	1	1	1
4E	1	1	1	1	1	1	1	1	0	1	0	1	1	1	1	1
4A	1	1	1	1	1	1	1	1	0	0	1	1	1	1	1	1
5S	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
5P	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
6BI	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
6N	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0
6HP	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	1

Based on the Spanish energy regulation [34], and the information available on the web site of the energy rating registrations, this study has considered categorizing the buildings of the case study according its energy rating. The building energy rating system is defined by the existing Spanish Technical Building Code, which, according the location (directly related to the climatic zone) and type of building (single family or apartment block), several values for each residential building category are defined: heating demand, cooling demand, global warming potential emissions or primary energy demand. Please note that, for residential buildings, this regulation does not define any constructive or energetic characteristics and it is simplified to a definition of the final energy demand or emissions of GWP value. Table 3 depicts the Heating Demand (HD) per square meter of Heated Floor Area (HFA) for each building category and for the specific location of the climate zone of the city of Donostia-San Sebastian of the case study. Then, Table 4 presents the main parameters characterizing each energy refurbishment strategy. As a result from the widely recognized energy simulation tool Energyplus [36] using the International Weather for Energy Calculation [37], the energy demand reduction (ER) related to the baseline has been calculated for passive strategies and per building category (C, D, E, F, G). Similarly, based on the British Standard EN 15316-4-3: 2007 [38], the energy production (EP) per square meter has been calculated for renewable strategies [39]. For active strategies, their energy performance (ρ_f) has also been defined [40]. Furthermore, the cost value of each strategy per square meter $c(k)$ is also described based on related literature [41–44]. In order to calculate the reduction of energy use achieved by different energy conservation measures, some correction factors (Table 6) are considered for the assessment of different energy conservation measures in the same scenario.

Table 3. Heating Demand (HD) per building category (kWh/m^2·a) [34].

	C	**D**	**E**	**F**	**G**
HD	48.7	81.6	144.1	157.1	212.1

Table 4. Main parameters characterizing each energy refurbishment strategy.

RS–Passive	**ER—Energy Demand Reduction (%)** [39] **Building Category (BC): C-D-E-F-G**	**c—Cost (€/m^2)** [40,41]
1B	19-21-23-25-26	143.4
1E	27-30-33-36-38	148.2
1A	33-36-40-43-46	185.3
2B	14-15-17-18-20	34.3
2E	24-26-29-31-33	38.5
2A	32-34-38-41-44	53.2
3B	12-14-15-16-17	29.8
3E	22-24-27-29-31	33.2
4B	11-12-13-14-15	198
4E	17-19-21-23-24	217
4A	22-23-26-28-30	380
RS—Renewable	**EP—Energy Production (kWh/m^2·a)** [39]	**c—Cost (€/m^2)** [43,44]
5S	454 (thermal energy)	437.2
5P	171 (electricity)	265.3
RS—Active	ρ_f**—Energy Performance** [40]	**c—Cost (€/m^2)** [40,41]
6BI	0.87	60
6N	1.1	19.22
6HP	3.27 (cooling COP) and 3.1 (heating COP)	50

Together with the properties of each of the refurbishment strategies, it should be noted that each of them is directly linked to different strengths, weaknesses and barriers (Table 5). As can be seen in Table 5, according to the objectives set by the stakeholder or the barriers of each case study, the applicable strategies will be different, allowing for generating a first scenario of strategies to be evaluated.

Table 5. Strenghts (S), weaknesses (W) and barriers (B) of each of the refurbishment strategies.

Strenghts (S), Weaknesses (W) and Barriers (B)	**1**	**2**	**3**	**4**	**5S**	**5P**	**6N**	**6BI**	**6HP**
Energy demand reduction (S)	X	X	X	X					
Increase the thermal confort of the habitants (S)	X	X	X	X					
Improvement of the building aesthetic performances (S)	X								
Applicable at protected buidlings (S)		X	X	X	X	X	X	X	X
Compatible with almost all the heat support systems (S)	X	X	X	X	X	X			
The solar resource is virtually unlimited (S)					X	X			
The solar energy conversion has no emissions (S)					X	X			
Reduction of the energy consumption and bill (S)	X	X	X	X			X		X
Reduction of the environmental emissiones (S)	X	X	X	X	X	X		X	
High cost (W)	X								X
Not applied in protected areas (W)	X			X	X	X			
Change of all internal objects or remove them for the installation (W)		X	X						
Loss internal space of the houses (W)		X							
Inaccuracy during the construction process (W)			X		X				
Difficulties in the store of thermal or electric energy (W)					X	X			
Need some space to store the fuel (W)								X	
Maximum value façades can grow externally (B)	X								
Legal classification of plot doesn't allow to intervene (B)	X				X	X			
Access to natural gas (B)							X		
Functional space/surface to implement (B)					X	X		X	X

3. Proposed Two-Stage Multi-Objective Meta-Heuristics

This paper presents two different two-stage multi-objective approaches based on the NSGA-II and the MOHS in order to provide: (1) Stage 1: *Building level optimization* that maximizes the Energy Consumption reduction (R_{EC}) while minimizing the Investment Cost (IC); (2) Stage 2: *District level optimization* aimed at maximizing the GWP reduction (R_{GWP}) while minimizing the total Payback Time (PT).

Thus, Figure 1 depicts the proposed methodology for optimizing (NSGA-II, MOHS) each building category (C, D, E, F, G) and obtaining the percentage of application of each Refurbishment Strategy (RS). Then, once the building level optimization is accomplished, a district level optimization (by means of the MOHS) is performed for obtaining the optimal combinations per building category that achieve the best performance at district scale. Note that building category corresponds to the energy performance rating defined by the Spanish Building regulation [27], *C* having a better energy performance (lower energy demand) than *D* and so on.

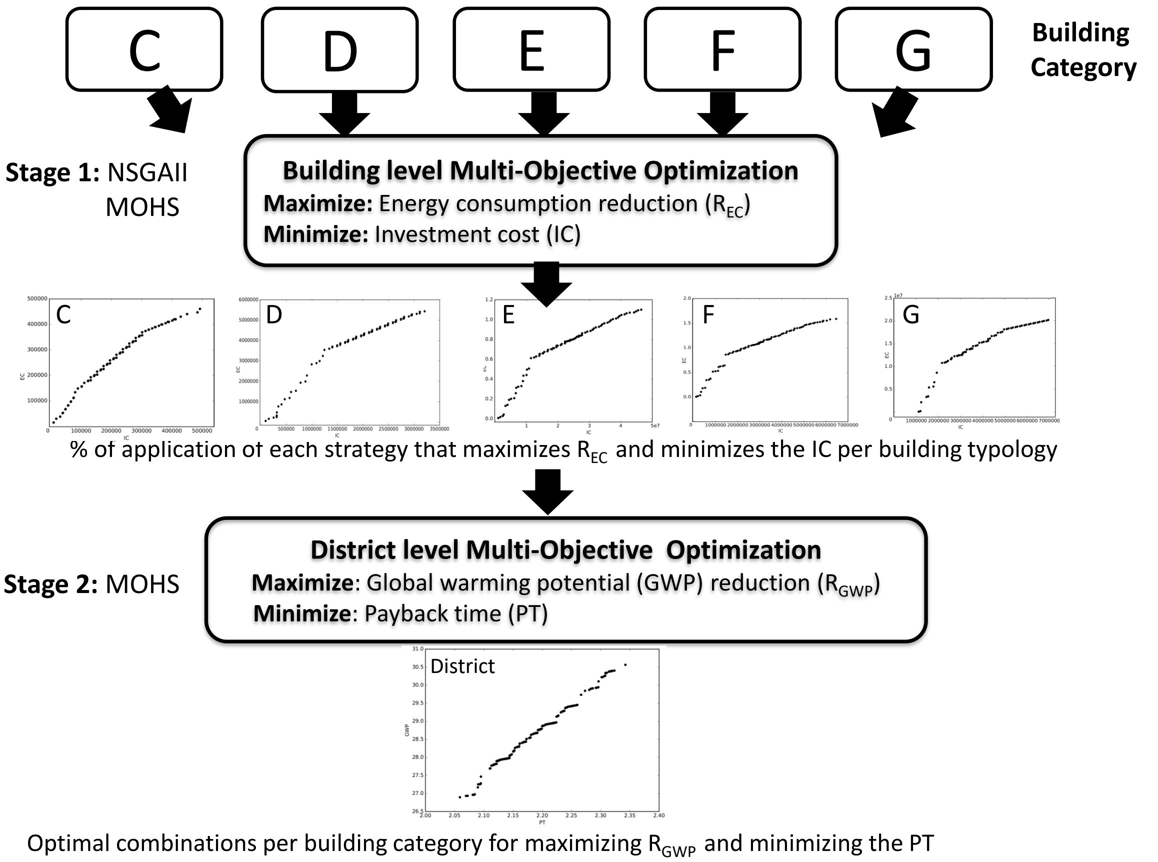

Figure 1. Proposed two-stage multiobjective approaches: (1) Building level optimization and (2) District level optimization.

3.1. Stage 1: Building Level Optimization

As previously stated in Section 3, this paper focuses on a two-stage multi-objective optimization that is performed firstly at building level and secondly at district scale based on the outputs of the first stage optimization per building category (C, D, E, F, G).

This section presents two different multi-objective algorithms based on the NSGA-II and the MOHS that simultaneously optimizes two (possibly conflicting) fitness functions at building level: IC and R_{EC}. Thus, the proposed multi-objective algorithms do not converge towards a unique solution; a set of solutions which represent good trade-offs (related to the bi-objective optimization) that comprise the *Pareto optimal* front is proposed instead.

In order to lay the foundations of the proposed meta-heuristics, the Harmony Search (HS) algorithm was first proposed by Zong et al. in [45] and afterward utilized for tackling diverse applications and problems that range from the Combined Heat and Power Economic Dispatch problem (CHPED) [46], Telecommunications [47–49], the Traveling Salesperson Problem (TSP) [45], Tour routing [50], Sudoku puzzle solving [51] and the optimal distribution of 24 h emergency units [52], among others. Similarly, the Genetic Algorithm (GA) in its multi-objective version NSGA-II was first proposed by Kalyanmoy in [53] and applied to different problems, such as: the Economic and Emission Dispatch Problem [54] and the Vehicle Routing Problem [55].

Both multi-objective approaches are population-based algorithms in which a set of candidate solutions $\{\mathbf{P}(k)\}_{k=0}^{K}$ are iteratively improved by means of the application of certain probabilistic operators. Following the notation stated, it will be hereafter denoted each possible candidate solution $\mathbf{P}(k)$ for the MOHS as *harmony* and for the NSGA-II as *chromosome*, whereas each of the N entries of such vector is called *note* for MOHS and *gene* for the NSGA-II. Within this optimization problem, each harmony/chromosome states the energy refurbishment strategy to be applied per building category $BC \in \{C, D, E, F, G\}$ and each note/gene indicates the percentage of application $p(k) \in \{0, 10, \ldots, 100\}$% of each refurbishment strategy $RS \in$ {1B, 1E, 1A, 2B, 2E, 2A, 3B, 3E, 4B, 4E, 4A, 5S, 5P, 6BI, 6N, 6HP}, as it is exemplified in Figure 2.

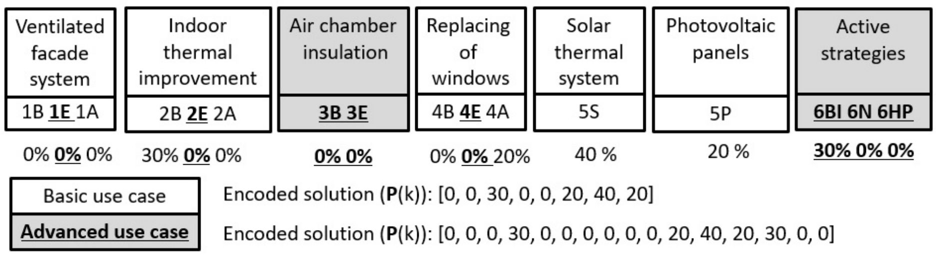

Figure 2. Example of encoding for basic and advanced use cases considering the applicable Refurbishment Strategies (RS) per case.

This candidate vector represents a refurbishment solution that involves a 30% of application of an indoor thermal improvement strategy (2B), a 20% of windows' replacement with low-emissivity coated glazing and wooden frames (4A). With regard to the renewable strategies, the implementation of solar and photovoltaic panels in the 40% and 20% of the total useful roof surface, respectively. Finally, it considers the 30% of application of Biomass boilers (6BI) as new energy generation technologies. Note that two different use cases are considered: basic and advanced. For the advanced use case, new refurbishment strategies such as efficiency levels (1E, 2E, 4E), air chamber insulation (4), and active strategies (6) are included.

It is important to remark that an independent optimization process is executed per building category $\in \{C, D, E, F, G\}$. Thus, five different populations ($\mathbf{P}$) are iteratively optimised in parallel in order to obtain optimal approximations of the Pareto frontier per building category as exemplified in Figure 1.

The improvisation procedure of the MOHS is driven by three parameters that will be explained below in step B1: (1) the *Harmony Memory Considering Rate*, HMCR; (2) the *Pitch Adjusting Rate*, PAR and (3) the *Random Selection Rate*, RSR. NSGA-II, however, considers the crossover and the mutation operators described in step B2. After generating new candidates, the quality of such new solutions is analyzed in terms of the objective functions (Investment Cost (IC) and reduction of the Energy Consumption (R_{EC})) and the best K melodies—among the newly produced ones and the ones stored in the HM from the previous iteration—will be kept for the next iteration. The entire process is repeated until a fixed number of iterations $\mathcal{I}$ is completed. Concretely, the steps of the proposed multi-objective algorithms are the following:

A. The **initialization** step is just executed once; at the first iteration the N entries of $\mathbf{P}(k)$ are randomly generated within the range {0, 10,. . . , 100}. It is important to remark that the constraints of the District Energy Retrofitting problem must be met, i.e., the simultaneous application of the refurbishment strategies must accomplish the symmetric matrix (Table 2) and the application of renewables strategies cannot exceed the total useful roof surface per building category.

B1. The **improvisation** process of the **MOHS** is composed by three different probabilistic operators that are sequentially applied to each note of the harmonies in order to produce a new improved set of K harmonies. Note that the probabilistic operators have been specially designed for this Energy Retrofitting problem:

- The Harmony Memory Considering Rate, HMCR $\in [0, 1]$, sets the probability that the new value for a certain note is randomly selected among the values of the same note in all the other $K - 1$ harmonies. That being so, the percentage of application of each refurbishment strategy per building typology is combined with the information of the remaining harmonies.
- The Pitch Adjusting Rate, PAR $\in [0, 1]$, aims at introducing subtle modifications in the harmony by establishing the probability that the new value for a given note is taken from its neighbouring values, instead of among the values stored in the HM. Thus, a step of 10% is added or subtracted with probability $\frac{1}{2}$, so as to apply slight changes in the new improvised solution. Note that the PAR is only employed in notes with values distinct to zero. Therefore, until this step, no new refurbishment strategy is generated.
- The Random Selection Rate, RSR $\in [0, 1]$, sets the probability to generate a random value for the new note from $[0, 10, \ldots 100]$. Thus, refurbishment strategies can be deleted or newly generated after the employment of this operator.

B2. The **improvisation** process of the **NSGA-II** is composed of two different probabilistic operators that are sequentially applied to each gene of the chromosomes in order to produce a new improved set of K chromosomes:

- The One Point Crossover operator, $\in [0, 1]$, sets the probability to interchange the knowledge from a previously selected mother and father chromosome in order to create the new offspring.
- The Mutation operator, $\in [0, 1]$, sets the probability to obtain a random value for the new gene from $[0, 10, \ldots 100]$. Thus, refurbishment strategies can be deleted or newly generated after the employment of this operator.

Note that, during the improvisation process, the level of compliance of the newly improvised solutions is checked in order to determine if the generated set is valid in terms of the combination of refurbishment strategies. For example, regarding the renewable strategies, it must be checked that the sum of the total useful roof surface is less than or equal to 100% and in all cases the district strategies' constraints (Table 2) must be fulfilled.

C. **Evaluation**: The new harmonies are *evaluated* in terms of Investment Cost (IC) Equation (1) and Reduction of Energy Consumption (R_{EC}) Equation (2). These fitness functions have been selected in order to seek for retrofitting solutions that intelligently cope up with the trade-off between cost (IC) and benefit (R_{EC}) per building typology:

$$IC = \sum_{k=1}^{K} p(k)\ c(k)\ A, \quad A \equiv \begin{cases} OFS\,(m^2) & \text{if } k \leq 2; i.e.,\ RS \in \{1B, 1E, 1A, 2B, 2E, 2A, 3B, 3E, 3A\}, \\ OS\,(m^2) & \text{if } 3 \leq k \leq 5; i.e.,\ RS \in \{4B, 4E, 4A\}, \\ TURS\,(m^2) & \text{if } 6 \leq k \leq 7; i.e.,\ RS \in \{5S, 5P\}, \\ HFA\,(m^2) & \text{if } k \geq 8; i.e.,\ RS \in \{6BI, 6N, 6HP\}, \end{cases} \tag{1}$$

where $p(k)$ is a certain note/gene which denotes the percentage of application of a refurbishment strategy, $c(k)$ the cost value of the refurbishment strategy and A represents the area of available surface for the strategy, i.e., Opaque Façade Surface (OFS) (1, 2 and 3), Opening Surface (OS)

(4B, 4E, 4A), Total Useful Roof Surface (TURS) (5S, 5P) or Heated Floor Area (HFA) (6BI, 6N, 6HP). The values for these parameters are defined in Section 3; $c(k)$: Table 4 and Section 4; A: Tables 9 and 12.

As stated in Equation (2), the Reduction of Energy Consumption (R_{EC}) is calculated as the sum of reduction of energy consumption related to passive (R_{EC_p}), renewable (R_{EC_r}) and active (R_{EC_a}) strategies implementation. It is important to note that R_{EC} is expressed in terms of non-renewable Cumulative Energy Demand (CED) [56] (Equation (4)). Likewise, Equation (5) stands for the reduction of energy consumption of passive (R_{EC_p}), renewable (R_{EC_r}) and active (R_{EC_a}) strategies.

When the method considers the application of a unique passive strategy, the 100% of energy demand reduction (ER) defined in Table 3 is considered. However, when the refurbishment scenario considers the application of two passive strategies, the method integrates the corrections factors defined in the following Table 6, which were calculated in [39]. This correction factor (cf) makes possible the assessment of different energy conservation measures in the same scenario (see Equation (3)):

Table 6. Corrections factors considered for the assessment of different energy conservation measures in the same scenario.

	1B	**1E**	**1A**	**2B**	**2E**	**2A**	**3B**	**3E**	**4B**	**4E**	**4A**
1B	1	-	-	-	-	-	-	-	0.94	0.93	0.91
1E	-	1	-	-	-	-	-	-	0.95	0.95	0.93
1A	-	-	1	-	-	-	-	-	0.96	0.95	0.94
2B	-	-	-	1	-	-	-	-	0.91	0.89	0.87
2E	-	-	-	-	1	-	-	-	0.92	0.91	0.90
2A	-	-	-	-	-	1	-	-	0.95	0.93	0.93
3B	-	-		-	-	-	1	-	0.89	0.89	0.87
3E	-	-	-	-	-	-	-	1	0.92	0.91	0.90
4B	0.94	0.95	0.96	0.91	0.92	0.95	0.89	0.92	1	-	-
4E	0.93	0.95	0.95	0.89	0.91	0.93	0.89	0.91	-	1	
4A	0.91	0.93	0.94	0.87	0.90	0.93	0.87	0.90	-	-	1

$$R_{EC} = R_{EC_p} + R_{EC_r} + R_{EC_a}, \tag{2}$$

$$R_{EC_p} = (R_{EC_{p1}} + R_{EC_{p2}}) \cdot cf, \tag{3}$$

$$R_{EC} = ES \cdot f_{CED}, \tag{4}$$

$$R_{EC_p} = ES_p \cdot f_{CED}; \;\; R_{EC_r} = ES_r \cdot f_{CED}; \;\; R_{EC_a} = ES_a \cdot f_{CED}, \tag{5}$$

where ES denotes the Energy Savings in terms of final energy consumption (kWh of Electricity or Natural gas); ES_p (Equation (6)) for passive strategies, ES_r (Equation (7)) for renewables and ES_a (Equation (8)) for active strategies. The factor f_{CED} allows for taking into account the primary energy content of the fossil fuel substituted (i.e., 4.428 MJ/kWh for natural gas and 6.264 MJ/kWh for electricity).

It is important to note that R_{EC} is expressed in terms of non-renewable Cumulative Energy Demand (CED) [56] (Equation (4)). Likewise, Equation (5) stands for the reduction of energy consumption of passive (REC_p), renewable (REC_r) and active (REC_a) strategies:

$$ES_p = \sum_{k=0}^{K} \frac{p(k) \cdot ER(k) \cdot HD \cdot HFA}{\rho_i} \;\; (kWh), \tag{6}$$

$$ES_r = \sum_{k=0}^{K} \frac{p(k) \cdot EP(k) \cdot TURS}{\rho_i} \;\; (kWh), \tag{7}$$

$$ES_a = \sum_{k=0}^{K} p(k) \cdot (HD \cdot HFA - ES_p) \cdot (\frac{1}{\rho_i} - \frac{1}{\rho_f(k)}) \;\; (kWh), \tag{8}$$

where ER represents the % of energy demand reduction related to the implementation of the passive strategy (Table 4), HD stands for the current Heating Demand per building category (Table 3), HFA remains the Heated Floor Area per building category (Tables 9, 11 and 12), EP corresponds to the Energy Production per square meter (Table 4), $TURS$ refers to the Total Useful Roof Surface per building category (Tables 9, 11 and 12), ρ symbolizes the performance of the thermal generation system (ρ_i for the current state (0.99 for Electric Boiler and 0.7 for Natural Gas Boiler) and ρ_f related to the active strategy implemented (Table 4)).

D. **Multi-objective sorting**: Once the quality of the fitness functions is evaluated as established in Equations (1) and (2), each solution is assigned with two new values: *the rank and the crowding distance*. Then, as explained in [53], each newly generated harmony is associated with a rank equal to its non-dominance level. Then, a specific crowding measure representing the sum of distances to the nearest harmony/chromosome along each objective is used to define an ordering among the solutions. In order to remain stored in the HM for the next iterations, solutions with less rank value and the largest crowding distance value are preferred. If two different solutions have the same rank, i.e., belong to the same front, then the point located in a region with less solutions (larger crowding distance) is preferred. The main idea is to select the solutions that optimise both metrics while providing a wider Pareto front formed by diverse solutions.

E. **Stop criterium**: The entire process continues until the *maximum number of iterations* $\mathcal{I} = 20$ is completed. Thus, while $nIter < \mathcal{I}$, the algorithm continues iterating, sets $nIter = nIter + 1$ and returns to step B (B1 for MOHS and B2 for NSGA-II). However, in the last iteration, the algorithm stops and the set of solutions stored in the memory that conform the dominant Pareto front is provided as possible results.

3.2. District Level Optimization

Once the building level optimization vian MOHS or NSGA-II is employed for each building category $\in \{C, D, E, F, G\}$, a district level optimization strategy by means of an MOHS is performed. Note that the result of the building level optimization is a Pareto front per building category and now non-dominated Pareto optimal solutions at district scale are sought in terms of district global metrics: the minimization of the Payback Time (PT) in Equation (9) and the maximization of the reduction of the Global Warming Potential (R_{GWP}) in Equation (10):

$$PT = \frac{IC}{ES_p \cdot f_e + ES_a \cdot f_e + ES_r \cdot f_e} \;\; (years), \tag{9}$$

$$R_{GWP} = \frac{ES_p \cdot f_{GWP} + ES_a \cdot f_{GWP} + ES_r \cdot f_{GWP}}{GWP_b} \cdot 100 \;\; (\%), \tag{10}$$

where f_e stands for the cost of the natural gas (0.0857 €/kWh) or electricity (0.219 €/kWh), f_{GWP} denotes the GWP factor per fuel type (i.e., natural gas (0.204 kg CO_2-eq/kWh), electricity (0.308 kg CO_2-eq/kWh) and GWP_b, which represents the GWP of the baseline scenario calculated per district and considering buildings' energy consumption related to heating, cooling, Domestic Hot Water (DHW), lighting and appliances multiplied by f_{GWP}.

The steps of the MOHS algorithm at district level are similar to the ones presented in the building level optimization but different initialization, improvisation operators and codification is used in this case (see Table 7).

The harmony memory is initialized at the first iteration in which the entries are randomly generated within the range $[0, 1, \ldots, Np\{i_{BC}\}]$. $Np\{i_{BC}\}$ represents the number of non-dominated solutions encountered per building category $i_{BC} \in \{C, D, E, F, G\}$.

Table 7. Example of a Candidate Solution (CS) that represents the selected solutions per Building Category (BC) ($i_{BC} \in \{C, D, E, F, G\}$), which optimizes the trade-off between the Payback Time (PT Equation (9)) and the reduction of the GWP (R_{GWP} Equation (10)) at district level.

BC	C	D	E	F	G
CS	12	20	33	2	35

This candidate solution at district level represents the value of the refurbishment solution selected per building category $\in \{C, D, E, F, G\}$ for which district global metrics in Equations (9) and (10) are optimized. By this way, each solution at district level is composed of different solutions at building scale.

The improvisation operators at district level are the following:

- The Harmony Memory Considering Rate, HMCR $\in [0, 1]$, sets the probability that the newly improvised note is randomly chosen among the values of the same note in all the other $K - 1$ harmonies.
- The Pitch Adjusting Rate, PAR $\in [0, 1]$ aims at introducing subtle modifications in the harmony by establishing the probability that the new value for a given note is taken from its neighbouring values, instead of among the values stored in the HM. Thus, a step of 1 is added or subtracted with probability $\frac{1}{2}$, so as to apply slight changes in the new improvised solution.
- The Random Selection Rate, RSR $\in [0, 1]$, sets the probability to pick a random value for the new note from the subset $[0, 1 \ldots Np\{i_{BC}\}]$.

4. Case Studies Definition

In this section, the definition of the different case studies is presented. These corresponds to the Gros and the Historical City Center districts in the city of Donostia-San Sebastian. Related to the Historical City Center district, a simple and an advanced case study are defined in order to analyse different degrees of complexity in the presented Energy Retrofitting problem.

4.1. Gros District Case Study Definition

The first case study proposed in this work embraces the district of Gros shown in Figure 3. This district is selected for being a representative district of the city in which different buildings with a mix of uses within the ground floors (commercial, garages and small industries) are being gradually replaced by new residential buildings.

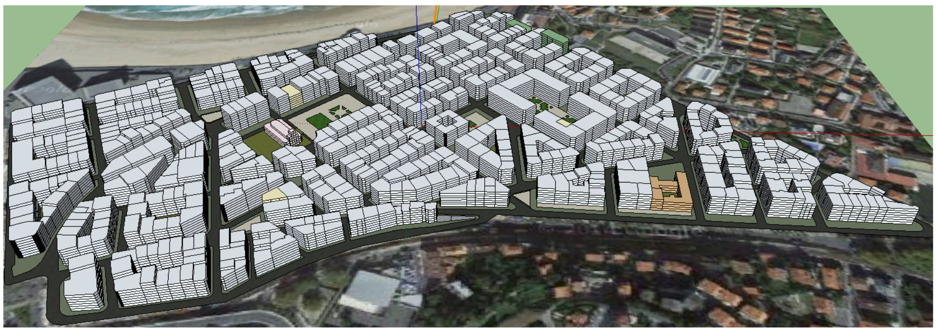

Figure 3. Gros district use case. The modelization and the environmental assessment has been obtained by a NEST tool [57].

Most of the information required for modeling the baseline scenario of Gros has been obtained in close collaboration with the municipality of Donostia-San Sebastian and based on assumptions from previous studies [57], as shown in Table 8.

Table 8. Gros district general data, building characteristics and available surface for renewable strategies.

Gros District: General Data	
Location	Donostia-San Sebastian
Climate zone	D1 [34]
District users	20,093
Total surface of the district	1,153,443 m^2
Dwelling surface	1,126,050 m^2
Tertiary building surface	8299 m^2
Other activities	17,512 m^2
Energy labelling–rating	C, D, E, F and G [58]
Heating and DHW system	Natural gas and electricity
Renewable generation	None
Architectural protection grade	Some buildings, grade 0–4 (according urban rules)
Total roof surface	159,964 m^2
Maximum useful roof surface for solar technologies	50,726 m^2

Regarding the buildings' information, such as: the energy rating, heating system or heritage protection level, Table 9 shows the main characteristics required as inputs for simulating the use case, i.e., HFA, useful roof or opening and opaque façade surface. For that purpose, the residential buildings considered in the study have been grouped in categories according to the energy labelling rating, as stated in Table 9. The systems considered for the estimation of heating and DHW consumptions are natural gas boilers. Finally, due to the climatological conditions in Donostia-San Sebastian, the residential buildings are not equipped with cooling systems.

Table 9. Main information of Gros district per building category. (HFA—Heated Floor Area, OFS—Opaque Facade Surface, OS—Openings Surface, TURS—Total Useful Roof Surface).

# Blocks	**Building Category**	**Use**	**HFA (m^2)**	**OFS (m^2)**	**OS (m^2)**	**TURS (m^2)**
3	C	Residential	6671	1676	558	486
42	D	Residential	89,350	23,391	7797	3567
396	E	Residential	781,204	214,207	71,402	37,705
55	F	Residential	93,684	27,394	9131	4376
51	G	Residential	80,998	22,122	7374	4569

As it is explained in Table 9, actually the energy labeling level of the 92% of the buildings of Gros is less than D energy rating. Consequently, this fact reinforces the immediate need of tools as the proposed one for assessing different refurbishment strategies in order to improve energy and environmental performance of districts.

4.2. Historical City Center District Case Study Definition

The historical city center district (Figure 4) has been selected for its importance in the city of Donostia-San Sebastian. It is protected by various regulations, thus reducing the number of conceivable options in terms of energy refurbishment strategies. Consequently, a limited set of possible actions for the use of renewable technologies and envelope renovation plans can be proposed. However, due to the high number of energetically inefficient buildings, the energy improvement potential of the district is high enough for considering it as an important case study for energy retrofitting purposes in Donostia-San Sebastian.

Table 10 resumes the main information of the historical city center of Donostia-San Sebastian in terms of general data, building characteristics and available surface for renewable strategies.

Figure 4. Picture of the historical city center district use case. The modelization has been accomplished by the NEST tool [57].

Table 10. Historical city center district general data, building characteristics and available surface for renewable strategies.

Historical City Center District: General Data	
Location	Donostia-San Sebastian
Climate zone	D1 [34]
District users	18,145
Total surface of the district	274,318 m^2
Dwelling surface	233,240 m^2
Tertiary building surface	30,389 m^2
Other activities	13,427 m^2
Energy labelling—rating	C, D, E, F and G [58]
Heating and DHW system	Natural gas and electricity
Renewable generation	None
Architectural protection grade	Some buildings, grade 0–4 (according urban rules)
Total roof surface	259,795 m^2
Maximum useful roof surface for solar technologies	116,817 m^2

In order to assess the energy refurbishment potential of the historical city center district, simulation results for a *simple* and an *advanced* case study are performed. Table 11 sums up the main information per building category $\in \{C, D, E, F, G\}$ for the simple use case.

Table 11. Main information of historical city center district per building category $\in \{C, D, E, F, G\}$ in the simple case study. (HFA—Heated Floor Area, OFS—Opaque Facade Surface, OS—Openings Surface, TURS—Total Useful Roof Surface).

# Blocks	Building Category	Use	HFA (m^2)	OFS (m^2)	OS (m^2)	TURS (m^2)
21	C	Residential	44,836	24,813	8271	8974
6	D	Residential	60,038	20,652	6884	12,603
42	E	Residential	484,254	164,808	54,936	96,431
52	F	Residential	549,373	179,797	59,932	110,955
29	G	Residential	134,863	22,122	18,629	30,831

For the advanced historical city center district case study, eight new refurbishment strategies are included (1A, 2A, 3B, 3E, 4A, 6BI, 6NC, 6HP), hence increasing the complexity of the problem. Table 12 sums up the main information per building category for this advanced case study. Note that additional constraints related to the real useful roof surface, the building heritage, the functional space to implement biomass boilers (6BI) or the type of energy generation systems are considered. Similarly, the building category will consider the energy rating and the forbidden strategies (see last column in Table 12).

Table 12. Main information of historical city center district per building typology $\in \{C1, C2, D, E1, E2, F1, F2, G1, G2\}$ in the advanced case study. (HFA—Heated Floor Area, OFS—Opaque Facade Surface, OS—Openings Surface, TURS—Total Useful Roof Surface).

# Blocks	Building Category	HFA (m^2)	OFS (m^2)	OS (m^2)	TURS (m^2)	Forbidden Strategies
20	C1	43,604	24,475	8158	3763	1B, 1E, 1A, 5S, 6BI
1	C2	1232	337	112	173	1B, 1E, 1A
6	D	60,038	20,652	6884	5036	1B, 1E, 1A, 5S, 6BI
33	E1	438,949	147,926	49,308	44,643	5S, 6BI
9	E2	45,304	16,881	5627	3699	1B, 1E, 1A
33	F1	388,793	124,497	41,499	27,575	1B, 1E, 1A
19	F2	160,580	55,300	18,433	20,219	1B, 1E, 1A, 5S, 6BI
7	G1	20,927	9670	3223	2104	1, 2, 3, 5, 6BI, 6HP
22	G2	90,480	46,217	15,405	9602	1B, 1E, 1A, 5S, 6BI

5. Simulation Results at Building Level

5.1. Gros District Case Study Simulation Results at Building Level

In this section, simulation results of the proposed Multi-Objective Meta-heuristic Algorithms (MOHS, NSGA-II) for the case study of Gros are presented. Both approaches are designed for obtaining optimal refurbishment scenarios in terms of Investment Cost (IC) and Energy Consumption reduction (R_{EC}) applied to each building category.

The non-dominated district retrofitting solutions obtained per building category after 20 Monte Carlo simulations are depicted in Figure 5. The objective functions are given in terms of initial economic investment (IC) (€/m^2) for the avoided Energy Consumption (R_{EC}) (kWh/year·m^2). As it can be observed, in order to effectively compare the cost-effectiveness of each building category, IC and R_{EC} are normalized to units of surface (m^2).

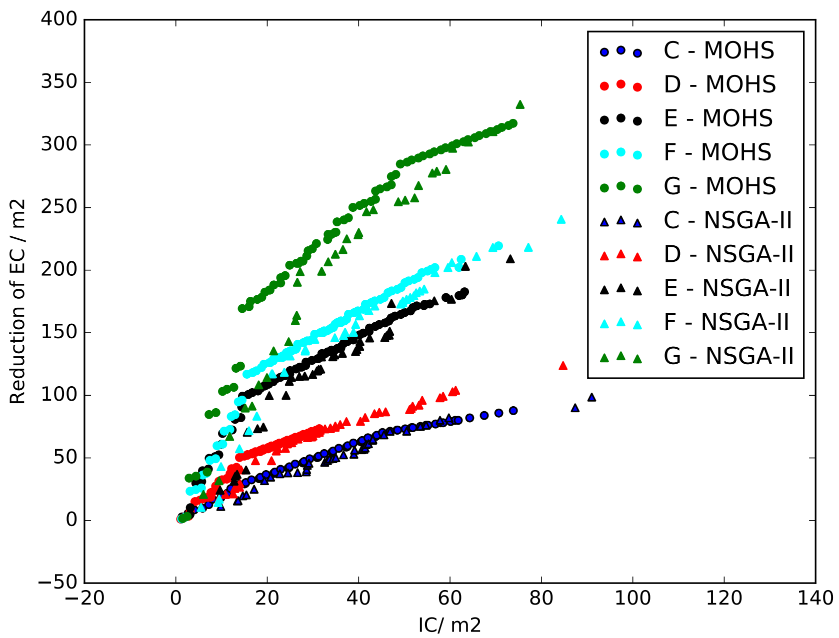

Figure 5. Estimated Pareto fronts obtained per building category in terms of IC (€/m^2) and R_{EC} (kWh/year·m^2).

As can be easily seen in Figure 5, building category *C* has currently the best energy performance, i.e., these buildings have a poor energy efficiency improvement potential, whereas category *G* has the highest energy refurbishment possibilities. The set of optimal refurbishment strategies achieved by MOHS and NSGA-II are depicted in Table 13, which corresponds to the interpretation of the solutions of the Pareto Fronts (Figure 5) per building category (BC).

Table 13. Optimal refurbishment strategies per building category $\in \{C, D, E, F, G\}$ achieved by the first optimization stage (NSGA-II and MOHS algorithms) in the Gros district—interpretation of the Pareto Fronts (Figure 5).

BC	Refurbishment scenario (**P**(k))
C	(10–100%) Internal (2A) + (10–100%) Solar Thermal (5S) + (10–100%) Replacement of windows (4)
D	(10–100%) Internal (2A) + (10–100%) Solar Thermal (5S) + (10%) Photovoltaics (5P) + (10–20%) Replacement of windows (4)
E, F	(10–100%) Internal (2A) + (10–100%) Replacement of windows (4) + (10–100%) Solar Thermal (5S) + Photovoltaics (5P)
G	(10–100%) Internal (2A) + (10–100%) Replacement of windows (4) + (10–100%) Solar Thermal (5S)

By means of analyzing in detail the evolution of the achieved optimal refurbishment strategies for C building category (Table 13) after the application of the proposed multi-objective approaches, the first strategy to be applied and henceforth the one that provides the highest R_{EC} / IC increment is the internal refurbishment strategy (2A). In this regard, solutions from 10 to 100% (i.e., 10–100%) of $2A$ are achieved by both multiobjective approaches. Once the 100% of this strategy is applied, the Solar Thermal (5S) panels are introduced until covering the 100% of the total useful roof surface and finally the replacement of windows is proposed. The achieved refurbishment scenarios for the remaining building categories (D–G) consider also the introduction of Photovoltaics jointly with Solar Thermal strategy in order to cover up to 100% of the total roof surface.

These conclusions—derived from the thoughtful analysis of the obtained solutions of MOHS and NSGA-II—can be visually adverted within the Pareto frontier (see Figure 5), as two trend variations or inflection points can be observed at 20 and 60 values of IC/m^2, respectively. In addition, the linear step variation of IC within the aforementioned three different stages corresponds to similar solutions (in which the same strategies are applied) but with an application increment of approximately 10% per refurbishment strategy. It is also worth mentioning that, for the lowest energy performance building categories (E–G), a bigger reduction of energy demand with passive strategies (and hence a higher slope in the first stage ($\text{IC}/\text{m}^2 \leq 20$) is obtained prior to the implementation of renewables.

The values of the probabilistic operators for both approaches have been optimized in order to obtain the best performance in the scenario of Gros, and are extended to the remaining use cases. Regarding MOHS, the values of the HMCR, PAR and RSR operators are set to 0.7, 0.3 and 0.1, respectively. NSGA-II employs crossover with probability of 0.3 and a mutation operator of 0.01.

In order to evaluate the quality of the approximated Pareto fronts obtained by MOHS and NSGA-II approaches, different complementary multi-objective performance metrics are employed in Table 14. On one hand, cardinality metrics such as the number of solutions that exists in the resultant Pareto Front is presented; intuitively, a high number of solutions—and hence a high value of such metrics—is preferred. Then, the coverage rate metric (%) is computed representing the number of solutions within each Pareto Front that are non-dominated by any solution in the rest of fronts. Finally, in terms of diversity metrics, hypervolume (HV) metric is computed following the Slicing Objectives (SO) procedure in [59].

As can be shown, MOHS obtains the highest number of non-dominated solutions for all building categories due to its explorative capability. Furthermore, the coverage rate metric indicates that MOHS encounters the greatest percentage of dominating solutions in its estimated Pareto front. Finally, Hypervolume indicator, which calculates the fraction of space covered by solutions in the objective space with respect to a cuboid given by reference points, also reveals a higher value when employing the MOHS approach as opposed to its NSGA-II counterpart. As argued before, MOHS has a better explorative behavior that permits achieving a wider range of solutions as can be graphically adverted in Figure 5. Nevertheless, MOHS requires more time to obtain the approximate Pareto frontier due to the higher complexity of its probabilistic operators.

Table 14. Number of non-dominant points, Coverage Rate and Hypervolume in the resulting Pareto Front per building category $\in \{C, D, E, F, G\}$ and multi-objective approach in the Gros district.

	Number of Non-Dominant Points	**Coverage Rate (%)**	**Hypervolume (HV)**
MOHS	{69,77,78,78,73}	{58, 63, 58, 65, 68}	{57.83, 59.38, 124.30, 156.24, 181.64}
NSGA-II	{39,45,39,40,33}	{6, 17, 5, 5, 0}	{6.05, 7.22, 19.02, 33.49, 38.54}

5.2. Simple Historical City Center District Case Study Simulation Results at Building Level

Table 15 summarizes the optimal refurbishment strategies encountered in the Pareto Front approximations of the simple historical city center district case study. It considers the same buildings categories $\{C, D, E, F, G\}$ of the Gros case study. Accordingly, the optimal refurbishment strategies per building category are similar to the ones obtained in the Gros district. The main difference is that, for building category C, no strategy based on the replacement of windows (4) is obtained. Hence, the implementation of Solar Thermal panels (5S) against façade refurbishment is prioritized in this case.

Regarding multi-objective performance indicators, Table 16 presents the achieved values for the number of non-dominant points, Coverage Rate and Hypervolume for MOHS and NSGA-II. As can be observed and following the analysis performed for the Gros district, best outcomes are in general obtained by the MOHS approach. Only NSGA-II achieves best results for the coverage rate metric in building categories D and E.

Table 15. Optimal refurbishment strategies per building category $\in \{C, D, E, F, G\}$ achieved by the first optimization stage (NSGA-II and MOHS algorithms) in the simple historical city center district case study.

BC	Refurbishment scenario (**P**(k))
C	(10–100%) Internal (2A) + (10–100%) Solar Thermal (5S)
D	(10–100%) Internal (2A) + (10–100%) Solar Thermal (5S) + (10%) Photovoltaics (5P) + (10–20%) Replacement of windows (4)
E, F, G	(10–100%) Internal (2A) + (10–100%) Replacement of windows (4) + (10–100%) Solar Thermal (5S)

Table 16. Number of non-dominant points, Coverage Rate and Hypervolume in the resulting Pareto Front per building category $\in \{C, D, E, F, G\}$ and multi-objective approach in the simple historical city center district case study.

	Number of Non-Dominant Points	**Coverage Rate (%)**	**Hypervolume (HV)**
MOHS	{69, 77, 78, 78, 73}	{66, 16, 13, 63, 71}	{70.16, 22.75, 64.81, 72.15, 52.91}
NSGA-II	{39, 45, 39, 40, 33}	{26, 31, 32, 14, 14}	{6.09, 7.97, 9.37, 13.66, 15.41}

5.3. Advanced Historical City Center District Case Study Simulation Results at Building Level

Regarding the advanced historical city center district case study, Table 17 presents the optimal refurbishment strategies per building category $\in \{C1, C2, D, E1, E2, F1, F2, G1, G2\}$ achieved by means of NSGA-II and MOHS. As can be observed, new strategies such as Natural Gas Condensing Boiler (6N), Heat Pump (6HP) and Biomass Boiler (6BI) are obtained in most of the building categories due to its capability of accomplishing a great reduction of energy consumption at low investment cost.

Table 17. Optimal refurbishment strategies per building category $\in \{C1, C2, D, E1, E2, F1, F2, G1, G2\}$ achieved by the first optimization stage (NSGA-II and MOHS algorithms) in the advanced historical city center district case study.

BC	Refurbishment scenario (**P**(k))
C1	(10–100%) Natural Condensing Boiler (6N) + (10–100%) Photovoltaics (5P) or (10–100%) Heat Pump (6HP) + (10–100%) Photovoltaics (5P)
C2	(10–100%) Internal (2,3) + (10–100%) Solar Thermal (5S) + (10–50%) Natural Condensing Boiler (6N)
D	(10–100%) Internal (2,3) + (10–100%) Natural Condensing Boiler (6N) or (100%) Heat Pump (6HP) + (10–70%) Photovoltaics (5P)
E1, F2	(10–100%) Internal (2,3) + (10–100%) Natural Condensing Boiler (6N) or (100%) Heat Pump (6HP) + (10–100%) internal (2,3) + (10-50%) Photovoltaics (5P)
E2, F1	(10–100%) Internal (2,3) + (10–100%) Natural Condensing Boiler (6N) or (70–100%) Biomass Boiler (6BI) + (10–100%) Solar Thermal (5S)
G1	(10–100%) Natural Condensing Boiler (6N) + (10–100%) Replacement of windows (4)
G2	(10–100%) Internal (2,3) + (10–100%) Natural Condensing Boiler (6N) or (100%) Heat Pump (6HP) + (10–100%) internal (2,3) + (10-100%) Photovoltaics (5P)

The main difference between $C1$ and $C2$ stands for the possibility of implementing Solar Thermal panels (5S) for the $C2$ building category. Furthermore, $C2$ proposes the façade refurbishment via internal (2) or air chamber (3) insulation. With regard to D building category, as 5S are not allowed (see forbidden strategies in Table 12), Internal Insulation (2, 3), Natural Condensing Boiler (6N) or Heat Pump (6HP) are proposed instead. Similarly to other case studies, E and F building categories achieve similar results. The biggest difference is that Biomass Boilers (6BI) and Solar Thermal panels (5S) cannot be implemented into $E1$ and $F2$ and Natural Gas Condensing Boilers (6N) or Heat Pumps (6HP) are proposed instead. Finally, related to G building categories, $G1$ involves the application of more constraints so in this case only the replacement of windows along with Natural Gas Condensing Boiler (6N) are prioritized by the proposed multi-objective approaches as optimal refurbishment strategies.

Following the same rationale of previous case studies, Table 18 shows the multi-objective performance indicators obtained per building category $\in \{C1, C2, D, E1, E2, F1, F2, G1, G2\}$ and multi-objective approach. As can be observed, apart from the number of non-dominant points for building category $C2$, all performance metrics renders better outcomes for the proposed MOHS approach.

Table 18. Number of non-dominant points, Coverage Rate and Hypervolume in the resulting Pareto Front per building category $\in \{C1, C2, D, E1, E2, F1, F2, G1, G2\}$ and multi-objective approach in the advanced historical city center district case study.

	Number of Non-Dominant Points	**Coverage Rate (%)**	**Hypervolume (HV)**
MOHS	{94, 95, 101, 99, 101, 94, 95, 26, 111}	{64, 44, 63, 55, 63, 57, 48, 49, 58}	{35.40, 11.83, 104.63, 201.52, 66.72, 80.21, 190.20, 87.79, 201.27}
NSGA-II	{53, 118, 58, 80, 45, 56, 66, 27, 60}	{8, 22, 8, 5, 3, 2, 10, 50, 2}	{9.14, 5.03, 13.64, 25.67, 9.06, 23.45, 21.76, 87.79, 32.61}

Due to the goodness of the multi-objective performance parameters obtained by the proposed MOHS, it is selected as a preferred multi-objective algorithm for tackling the energy retrofitting problem at building level, since the response time is not a limitation for this case.

5.4. Complexity Analysis

For a predefined maximum number of iterations, MOHS performs four operations: three probabilistic operations (HMCR, PAR, RSR) applied to each note of the harmonies and the evaluation of the population. On the other hand, NSGA-II employs only three operations: a one point crossover, a mutation and the evaluation of the population. The population size (K) and the number of iterations ($\mathcal{I}$) are the same for both approaches, so the number of metric evaluations is ($\mathcal{I} n_o K$), being n_o the number of objectives. Thus, it is expected that NSGA-II requires less computational time to complete the optimization process since its operators are less time-consuming than those of its counterpart.

Following the rationale of [60], the computational complexity of NSGA-II is $O(\mathcal{I} n_o K^2)$. As MOHS employs the same non-dominated sorting procedure as NSGA-II, the complexity of MOHS equals the one of the NSGA-II algorithm. To empirically verify the complexity analysis, Tables 19 and 20 compare the average execution time (s) of each algorithm per building category and district case study. Note that both multi-objective approaches have been executed in an Intel Core i7 CPU at 3.40 GHz, Spain.

From the results of Table 19, it can be observed that the execution time of NSGA-II is lower (almost 50%) than its MOHS counterpart for all building categories in the Gros and the simple historical city center district case studies. Nevertheless, for the advanced historical city center case study, this ratio decreases to 22%. In fact, it seems that, as long as the complexity of the case study increases, the execution time of the NSGA-II increases, whereas the execution time for the MOHS remains almost fixed. Thus, for more complex case studies, the execution time for MOHS would be the same or less than the expected for the NSGA-II.

Table 19. Average CPU Time (s) per Monte Carlo simulation for MOHS and NSGA-II per Building Category (BC) for the Gros District and the Simple Historical City Center District.

BC	Gros District CPU Time (s) (MOHS / NSGA-II)	Simple Historical City Center District CPU Time (s) (MOHS / NSGA-II)
C	1.346/0.661	1.332/0.546
D	1.347/0.718	1.373/0.758
E	1.362/0.723	1.363/0.551
F	1.331/0.676	1.347/0.583
G	1.409/0.582	1.394/0.598

Table 20. Average CPU Time (s) per Monte Carlo simulation for MOHS and NSGA-II per Building Category (BC) for the Advanced Historical City Center District Case Study.

BC	Advanced Historical City Center District CPU Time (s) (MOHS / NSGA-II)
C1	1.327/1.019
C2	1.299/1.035
D	1.357/0.957
E1	1.283/1.066
E2	1.357/1.035
F1	1.394/1.036
F2	1.322/1.004
G1	1.326/1.076
G2	1.373/1.113

6. Simulation Results at District Level

In this section, the best scenarios at district level are obtained based on the targets defined by Donostia-San Sebastian for 2030 of 30% of Global Warming Potential (GWP) reduction [61]. Nevertheless, this study has established 2016 as the baseline scenario and summed up the CO_2 eq. emissions related to heating, cooling, DHW, lighting and appliances.

Table 21 refers to the optimal refurbishment scenarios per building category achieved by the second stage multi-objective approach (MOHS) which optimizes the trade-off between GWP reduction R_{GWP} (Equation (10)) and Payback Time (PT) (Equation (9)) at district level. In order to select one optimal refurbishment scenario per building category, only those results from the first optimization stage that cope up with the 30% reduction of GWP at district level are selected. For each selected scenario, the obtained Payback Time (PT) is also shown.

Table 21. Optimal refurbishment scenarios obtained by the second optimization stage (MOHS algorithm) per building category (BC) which cope up with the 30% of reduction of Global Warming Potential at district level.

Gros District Case Study	
BC	Refurbishment scenario (**P**(k)) PT = 2.15 years
C	10% of internal insulation
D	80% of internal insulation and 20% of PV panels
E	90% of internal insulation and 10% of PV panels
F	100% of internal insulation, 10% of windows substitution and 10% of PV panels
G	100% of internal insulation, 90% of windows substitution and 10% of Solar thermal
Simple Historical City Center District Case Study	
BC	Refurbishment scenario (**P**(k)) PT = 2.57 years
C	10% of internal insulation and 10% of PV panels
D	90% of internal insulation
E	70% of internal insulation and 10% of PV panels
F	100% of internal insulation, 30% of windows substitution
G	100% of internal insulation, 80% of windows substitution and 10% of Solar thermal
Advanced Historical City Center District Case Study	
BC	Refurbishment scenario (**P**(k)) PT = 2.69 years
C1	20% of air chamber insulation
C2	30% of air chamber insulation and 20% of PV panels
D	100% of internal insulation
E1	90% of air chamber insulation and 40% of Natural Gas Condensing Boilers
E2	60% of air chamber insulation, 100% of Natural Gas Condensing Boilers and 20% of PV panels
F1	80% of internal insulation and 30% of PV panels
F2	100% of internal insulation and 20% of Natural Gas Condensing Boilers
G1	20% of windows replacement and 100% of Natural Gas Condensing Boilers
G2	90% of air chamber insulation and 100% of Natural Gas Condensing Boilers

As can be derived from the results, PT remains between two and three years in all case studies, which is a reasonable time period for amortizing the cost of investment of the proposed refurbishment strategies. Note that retrofitting scenarios proposed for Gros and the simple historical city center district are quite similar. This is due to the similarity in the building categories and proposed refurbishment strategies. Note that the ratio and number of strategies increase when the current building energy performance gets worse; the implementation of strategies for the *C* building category range from 10% to 30% façade insulation, whereas, for *G* building category, it reaches nearly 100% of façade insulation and 80% to 100% windows. For the advanced historical city center case study, different refurbishment scenarios are proposed due to the new constrained formulation of the district energy retrofitting problem.

7. Conclusions

This paper proposes two novel multi-objective algorithms (MOHS, NSGA-II) for tackling the district energy retrofitting problem. The optimization procedure is focused on a two-stage process in which real-based goals and constraints at building and district level are jointly considered. The developed multi-objective heuristics are applied to two real-based case studies: Gros and the historical city center of Donostia-San Sebastian with two different degrees of complexity. The achieved simulation results and multi-objective performance indicators elucidate the goodness of the proposed MOHS approach. It is capable of obtaining a wide range of feasible retrofit scenarios in terms of environmental and economic aspects allowing the selection of the optimal scenario at district level based on the targets defined by Donostia-San Sebastian for 2030 in terms of GWP reduction. In fact, up to a 30% of reduction of GWP at district level is obtained for a Payback Time (PT) of 2–3 years, which is a reasonable time period for amortizing the cost of investment of the proposed refurbishment strategies.

Future research lines will delve into quantifying other impacts directly related to refurbishment strategies. For example, most of the results show that the optimal cost-efficient passive strategy is the internal insulation or the air chamber insulation. However, these strategies do not solve some qualitative constructive pathologies, such as: the thermal bridges or the moisture problems. In addition, the improvement of the refurbished buildings' value can be also considered during the optimization process at building level. More precisely, even if the ventilated façade (1B, 1E, 1A) is not selected due to its high investment cost, the economic value of the building would be considerably increased, mainly due to the improvement of its external aesthetic. Therefore, for future studies, it could be interesting to integrate these additional indicators into the proposed MOHS optimization algorithm. Finally, the lack of information at city scale can be solved by the application of the proposed approach at representative districts for which relevant data is available. Thus, municipalities can employ the achieved results to easily generalize the decision-making process to districts with similar characteristics.

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