

INFLUENCE OF THE REPRESENTATIVENESS OF REFERENCE WEATHER DATA IN MULTI-OBJECTIVE OPTIMIZATION OF BUILDING REFURBISHMENT

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ABSTRACT

Energy saving measures properly applied to the existing building stock can bring noticeable savings. In particular, optimal cost-effective solutions can be found through multi-objective optimization techniques, such as those based on genetic algorithms (*GA*), coupled with building energy simulation (*BES*). Although the robustness of *GA* multi-objective optimizations to the quality of the inputs is discussed in the literature, the role of the weather data file is not investigated in detail. For this reason, this work analysed the extent to which the method adopted for the development of reference weather data for *BES* can affect the optimal solutions. Considering a group of simplified building configurations and the location of Trento, Italy, many multi-objective optimizations are performed. The results show changes to both Pareto fronts and optimal retrofit solutions.

INTRODUCTION

The European Commission suggested the renovation of existing buildings into nearly zero-energy buildings through the definition of cost-optimal levels into the framework of building energy retrofitting (European Commission, 2010 and 2012). Among all possible energy saving measures (*ESMs*), the one that optimizes some competitive goals - such as the contemporaneous minimization of net present value (*NPV*) and primary energy (*EP*), should be chosen. For this reason, multi-objective optimization and *BES* can help to determine a set of equivalent optimal solutions, the so-called Pareto front. In particular, among the different alternative strategies, such as those described by Evins (2013), the evolutionary optimization approaches - and especially the genetic algorithms, have become more and more popular (Penna *et al.*, 2015).

When dealing with imprecise input data, sensitivity issues can undermine the suitability of multi-objective optimization in finding cost optimal solutions. In this regard, while *GA* robustness to algorithm parameters has been widely investigated (Wright and Alajmi, 2005; Ihm and Krarti, 2012), the robustness to suboptimal inputs needs to be further discussed. In this context, reliable building simulation results depend also on the

representativeness of weather inputs, which can be sources of external scenario uncertainties (Hopfe and Hensen, 2011). In fact, both length of the multi-year weather data series (Prada *et al.*, 2014) and methodology used for the typical month selection largely influence the results of the reference year development process (Pernigotto *et al.*, 2014a; Pernigotto *et al.*, 2014b). Consequently, the cost optimal identification through *GA* optimization could be influenced as well and the findings could lack robustness to climate changes.

The aim of this work is to investigate the extent to which the weather data used for *BES* can affect the robustness of *GA* approach for multi-objective optimization and the identified optimal solutions. In this way, it has been possible to assess the sensitivity of the optimization method to an uncertain and suboptimal input such as the typical climatic file, which can be developed according to different approaches from the same sets of raw weather data.

METHODS

Several multi-objective optimizations have been carried out with different reference years, developed according to the methods described in (Pernigotto *et al.*, 2014b) from a set of hourly weather data series collected in the meteorological station of Trento, northern Italy. Various building configurations have been analysed to achieve results suitable to make generalization.

The implemented Genetic Algorithm

The choice of optimal trade-off between *EP* and *NPV* is based on the domination of a general solution *X* over a solution *Y*. According to Pareto, *X* dominates *Y* if the following conditions are both true:

- the solution *X* is no worse than *Y* in all objectives;
- the solution *X* is strictly better than *Y* in at least one objective.

Thus, passing from *X* to *Y*, an improvement for some objectives, without worsening the other ones, is supposed. When an objective cannot improve without making worse the others, an "Optimum of Pareto" is found. The two steps of the optimization procedure are therefore: (a) the definition of Pareto front and (b) the selection of a trade-off solution among those belonging to Pareto front.

For the multi-objective optimization of building retrofits, a GA is implemented in Matlab®. The Matlab® fitness function used in the analysis launches BES (TRNSYS BES, in this case), reads BES output file and post-processes the simulation results. The code computes the NPV by means of the method proposed by the technical standard EN ISO 15459:2009 (CEN, 2009) and returns the two objectives to the genetic algorithm. In particular, NPV and EP for space-heating (EP_h) are chosen as goals for the multi-objective optimization.

The genetic algorithm chosen in this work is Elitist Non-dominated Sorting Genetic Algorithm, NSGA-II (Deb, 2002), identified because of its better performance with respect to other GA algorithms (Brownlee *et al.*, 2011; Evins, 2013). Moreover, it has been modified with customized sampling, crossover, mutation and selection procedures. All these modifications, together with population size and crossover fraction, are adopted with the purpose of further increasing the genetic algorithm performances (Penna *et al.*, 2015). In the first step, the initial population, to which the genetic algorithm optimization is closely related, is selected. The Sobol sequence sampling is chosen since it produces uniform samples for high population sizes (Saltelli *et al.*, 2004; Burhenne *et al.*, 2011) and reduces the risk of oversampling. Moreover, the random starting point in Sobol sequence is obtained through a pseudo random generator (Matsumoto and Nishimura, 1998).

Once the fitness function is evaluated, the genetic algorithm proceeds with the selection of the best individuals (i.e., the “parents” for the next generation). In this study, the “Tournament Selection Without Replacement” (Goldberg *et al.*, 1989; Goldberg and Deb, 1991) has been adopted: a short list of four eligible parents are randomly chosen and, among them, the best individual is set to be a parent. Then, the genetic characteristics of both parents are combined, giving rise to the new generation. Children are a random (Matsumoto and Nishimura, 1998) arithmetic mean of two parents always feasible with respect to the bounds (Burjorjee, 2013). The adopted crossover fraction - i.e., the fraction of the next generation that crosses over, is set to 0.8. The remaining individuals in the next generation come from population mutation, randomly applied by means of Mersenne-Twister pseudo random generator (Matsumoto and Nishimura, 1998). Specifically, a gene is randomly selected and replaced by a random value from a uniform distribution that meets the gene range.

The convergence criterion is based on the crowding distance, i.e., the closeness of an individual to its neighbours (Deb, 2002). Specifically, multiple runs of the algorithm are performed until a change of 10^{-4} is found for the crowding distance between two consecutive generations (Jena *et al.*, 2013). The final population contains the optimal solutions.

Building case-studies

With the purpose of ensuring the result generalization, three typologies of building are simulated: semi-detached houses ($S/V = 0.97 \text{ m}^{-1}$), penthouses ($S/V = 0.63 \text{ m}^{-1}$) and intermediate flats in multi-story buildings ($S/V = 0.3 \text{ m}^{-1}$), obtained by imposing an adiabatic boundary condition whenever the envelope structures are adjacent to other apartments (Figure 1). Each building has 100 m^2 of floor surface, 3 m of internal height and façades oriented towards the main cardinal directions. If not adiabatic, the envelope surfaces are directly exposed to the external environment, without thermal contact with the ground for the floor of the semi-detached house. The considered configurations have windows only in one façade (East or South), which is also in front of the adiabatic vertical wall adjacent to other buildings. The window to floor ratio is equal to 0.144.

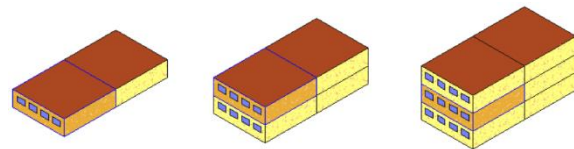


Figure 1 - Test cases used in robustness analysis

Table 1
Building characteristics

Opaque Envelope	Windows	Infiltration Rate
$d=0.20 \text{ m}$	Glazing: Single-pane	Intermediate flat
$\lambda=0.25 \text{ W m}^{-1}\text{K}^{-1}$	U_{gl} 5.69 [$\text{W m}^{-2}\text{K}^{-1}$]	0.06 ACH
$R=0.80 \text{ m}^2\text{K W}^{-1}$	SHGC 0.81	Semi-detached house
$\kappa=150 \text{ kJ m}^{-2}\text{K}^{-1}$	Frame: Standard timber	0.13 ACH
$\rho=893 \text{ kg m}^{-3}$	U_{fr} 3.20 [$\text{W m}^{-2}\text{K}^{-1}$]	Penthouse
$c=840 \text{ J kg}^{-1}\text{K}^{-1}$	A_{fr}/A_{win} 19.9	0.20 ACH

The thermal transmittances of opaque and transparent components have the typical values of the Italian building stock built before the first Italian energy saving law, law number 373 of 1976 (Table 1). The opaque envelope is a simplified massive structure with a clay-block and the glazing system includes a single-pane glass and a standard timber frame, modelled with LBNL Window 6.3. The linear thermal transmittances of thermal bridges are computed according to EN ISO 10211:2007 (CEN,

2007a) by means of LBNL THERM 6.3. The infiltration rates (Table 1) are estimated according to EN 12207:1999 (CEN, 1999) and EN 15242:2007 (CEN, 2007b), considering a reference air tightness n_{50} of 7 air changes per hour (ACH). As regards the system typically found in buildings built up to 1970s and not yet renovated, a standard boiler coupled with radiators and *ON-OFF* system regulation are considered.

Weather data

Representative weather information is essential for reliable building energy performance analyses. In particular, a reference year should be able to characterize the climatic conditions typical for the entire life cycle of the building. In the literature, many approaches can be found for the elaboration of the reference year, with results characterized by different levels of representativeness in the different climates (Pernigotto *et al.*, 2014b). In this work, it has been verified how the variability of reference weather file may affect the choice of optimal retrofit solutions for the city of Trento, North of Italy (Köppen classification: Cfa; ASHRAE 169/2006 classification: 4A). Six reference years are developed starting from an historic series of 10 years, according to the following methods: (M1) EN ISO 15927-4 (CEN, 2005), (M2) Wilcox and Marion's method (2008), (M3) the method by Pissimanis *et al.* (1988) and the three ones described in (Pernigotto *et al.*, 2014b) - (M4) the minimum Finkelstein-Schafer statistic, *FS*, (M5) Best rank I and (M6) Best rank II. These methods differ from each other because in the same historic series of 10 years they lead to select different representative months for the reference year. The different choice of representative months brings differences in Heating Degree-Days calculated with respect to a base temperature of 18 °C (HDD_{18}) and in daily average global solar irradiation on horizontal surface (I_{sol}), as shown in Table 2. In particular, the maximum HDD_{18} , obtained from the method M6, Best rank II, is 2504 K d and the minimum HDD_{18} , arising from the method M2 by Wilcox and Marion, is 2330 K d.

Table 2

Heating Degree-Days and daily average global solar irradiation on horizontal surface obtained with different methods for the reference year development

Method	HDD_{18} [K d]	I_{sol} [$MJ m^{-2} d^{-1}$]
M1	2499	7.98
M2	2330	7.65
M3	2496	7.27
M4	2448	7.70
M5	2484	7.50
M6	2504	7.49

Energy saving measures and economic analysis

In the multi-objective optimizations, six different types of *ESMs*, representative of the most common

solutions adopted by designers to reduce EP_h , are evaluated (Penna *et al.*, 2015; Prada *et al.*, 2014):

- an additional insulating layer of extruded polystyrene with a thermal conductivity of $0.04 W m^{-1} K^{-1}$ and thickness ranging from 0.01 to 0.20 m (with a step of 0.01 m), changed independently for the external surface of non-adiabatic walls, ceiling (only for semi-detached houses and penthouses) and floor (only for semi-detached houses);
- replacement of current windows with high performance frames with $U_{fr} = 1.2 W m^{-2} K^{-1}$ and glazings (i.e., double, *D*, or triple, *T*, glazings – respectively with $U_{gl} \approx 1.1 W m^{-2} K^{-1}$ and $U_{gl} \approx 0.6 W m^{-2} K^{-1}$, and either high, *H*, or low, *L*, solar heat gain coefficients of about 0.6 and 0.35, respectively);
- replacement of existing boiler (*STD*) with either modulating (*MOD*) or condensing boiler (*COND*). In both cases the new boiler is also equipped with an external climatic adjustment in order to vary the supply temperature as a function of the external air temperature;
- adding a mechanical ventilation (*MVS*) with heat recovery system.

Some other improvements are associated with the proposed measures. The addition of the external insulation mitigates the thermal bridges: thus, their linear thermal transmittance is recalculated and used in simulations. The windows replacements greatly increase air tightness and, thus, a reduction of 50 % is applied to the building infiltration rate. As a whole, the combinations of all possible alternative *ESMs* can be very high: in case of semi-detached houses, for example, more than 275 000 solutions need to be calculated in order to find the optimal one and this makes necessary the adoption of advanced multi-objective optimization techniques, such as the *GA* of the current research.

The prices adopted for the different *ESMs* have been taken from the official regional price list and the energy source prices are extracted from the database of the national authority of gas and electricity (Penna *et al.* 2015; Prada *et al.*, 2014). For the cost-optimal analysis the *NPV* has been computed as suggested by the regulation EU 244/2012 (European Commission, 2012). The investment analysis is 30-year long and includes the initial investment cost, the annual running costs (composed by energy and maintenance costs), the replacement cost due to periodic substitution of building elements and the residual value for the equipment with longer lifespan.

Building energy simulation

The annual primary energy for space heating demand EP_h has been calculated by means of TRNSYS hourly simulation. Each building has been modelled by means of TRNSYS Multizone Building subroutine "Type 56". The full Reindl correlation

(Reindl *et al.*, 1990) coupled with Perez projection model (Perez *et al.*, 1988) has been used to compute the solar irradiation incident to tilted surfaces. Subroutine “Type 869” (Haller *et al.*, 2011a; Haller *et al.*, 2011b) has been adopted to model the different heating systems. The heating system has been controlled by an *ON/OFF* thermostat (“Type 2”) that switches the boiler *ON* if the indoor air temperature is lower than 20 °C and *OFF* if the air temperature overcomes 22 °C. The pump power consumption has been modelled by means of TRNSYS subroutine “Type 3” while “Type 31” has been used to compute the distribution heat losses of pipes.

RESULTS AND DISCUSSIONS

Pareto fronts

Initial EP_h and NPV evaluated with the six reference years are reported in Table 3. As expected, the weather file composition affects both energy and economic performance of the initial existing buildings. The configurations with East-faced windows have the largest EP_h and NPV , approximately around +33 kWh m⁻² yr⁻¹ and +9000 €, as average, with respect to the corresponding cases with windows on the South façade. The buildings with $S/V = 0.97$ m⁻¹ have EP_h and NPV twice larger than those with $S/V = 0.30$ m⁻¹. The normalized standard deviations for both EP_h and NPV are similar. Considering the whole sample of buildings, the reference year M2 is the one with the largest deviation (-5.2 %) with respect to the average

performance of the six reference years, while M5 is the closest one (+0.7 %). These findings are coherent with those in (Pernigotto *et al.*, 2014b) for Trento, where Wilcox-Marion reference year gave the worst performance compared to the multi-year average heating needs while Best rank I gave the best one.

The Pareto fronts are represented in Figure 2. The graphs show the trade-off between NPV and EP_h obtained for the six reference years. Two groups of results belonging to the fronts can be distinguished: the optimal solutions with mechanical ventilation system in the higher-left side of the chart (i.e., with higher NPV and lower EP_h) and those with natural ventilation in the lower-right side (i.e., with lower NPV and higher EP_h). The variability of weather inputs is reflected in a shift of Pareto fronts. The front calculated with M2 is characterized by the lowest NPV and EP_h while the one estimated with M3 has often the highest NPV and EP_h of the group of six reference years. Indeed, Wilcox-Marion reference year leads to the prediction of a better energy performance of the initial configurations while reference year M3, developed according to Pissimanis *et al.*, a worse performance is indicated for most of configurations.

In some cases, there are also intersections of Pareto curves calculated from the different reference years, even if this behaviour seems less marked than the one observed in previous works in case of reference years developed with EN ISO 15927-4 method from historic series of different length (Prada *et al.*, 2014).

Table 3

Annual primary energy for space heating and net present values for the initial existing buildings according to the six different reference years

EP_h [kWh m ⁻² yr ⁻¹]									
S/V	Orientation	M1	M2	M3	M4	M5	M6	Avg.	Std. dev.
0.30	East	154.2	143.2	154.6	149.6	153.3	153.3	151.4	2.9 %
	South	119.7	106.5	122.1	112.6	116.7	116.9	115.8	4.8 %
0.63	East	231.9	217.6	230.8	225.3	229.2	230.1	227.5	2.3 %
	South	197.9	181.9	200.4	190.3	194.6	195.5	193.4	3.4 %
0.97	East	294.7	280.9	292.7	288.7	291.9	292.9	290.3	1.7 %
	South	264.9	248.2	266.8	256.7	260.8	261.9	259.9	2.6 %
NPV [€]									
S/V	Orientation	M1	M2	M3	M4	M5	M6	Avg.	Std. dev.
0.30	East	42 666	39 658	42 764	41 406	42 415	42 426	41 889	2.9 %
	South	33 283	29 672	33 910	31 347	32 456	32 502	32 195	4.7 %
0.63	East	63 828	59 926	63 522	62 017	63 107	63 315	62 619	2.3 %
	South	54 553	50 227	55 233	52 485	53 671	53 896	53 344	3.3 %
0.97	East	80 910	77 180	80 360	79 292	80 178	80 448	79 728	1.7 %
	South	72 817	68 257	73 310	70 564	71 680	72 008	71 439	2.6 %

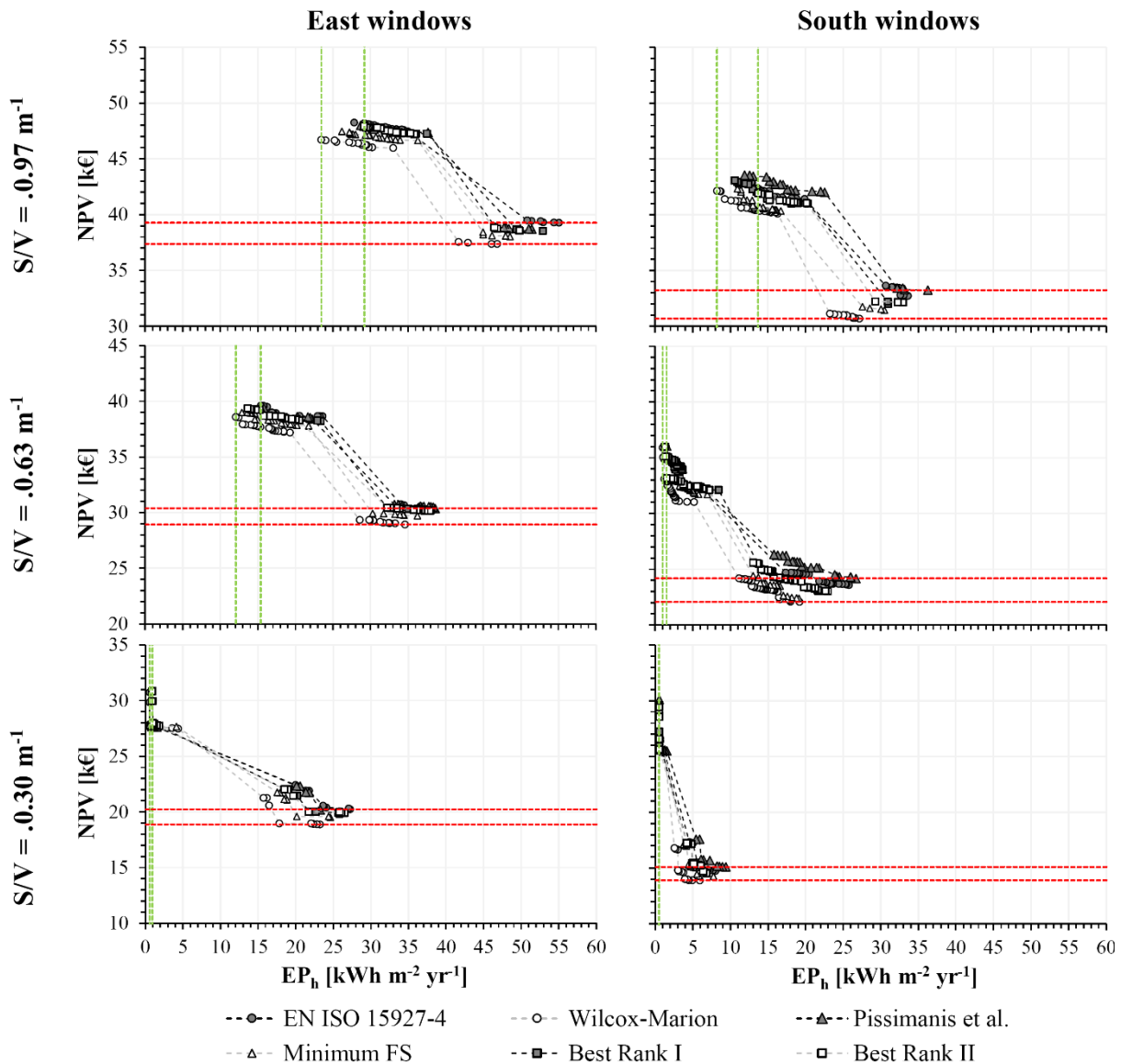


Figure 2 - Pareto fronts for the different building configurations. The green vertical lines delimitate the spread between the energy optima while the red horizontal lines the spread between the cost optima found with the six different reference years

For instance, in the case of $S/V = 0.63 \text{ m}^{-1}$ with South-faced windows, considering the group of configurations with natural ventilation, the Pareto front with highest NPV and EP_h is with the reference year M3, whereas for the group of configurations with mechanical ventilation the Pareto front with highest NPV and EP_h is with the reference year M5.

Cost optimal

In order to evaluate in detail the effects of the different reference years on the cost-optimal solution, the *ESM* configurations of Pareto front ensuring the minimum of a single objective have been analysed, starting from the *NPV*.

As it can be seen in Tables 4 and 5, the *ESMs* optimizing the economic objective are the adoption of double glazing and natural ventilation. The only exception is the semi-detached house with East-oriented windows, for which the reference year M3

leads to the recommendation of replacing the original windows with triple glazing. For cases with $S/V = 0.3 \text{ m}^{-1}$ and both East and South-faced windows and those with $S/V = 0.63 \text{ m}^{-1}$ and South-oriented windows, no substitution of the boiler is suggested. For the remaining configurations, the modulating boiler is preferred for buildings with South-faced windows and the condensing boiler for buildings with East-faced windows. For the latter, the reference year affects the choice of the new boiler: for instance, the penthouse can be optimized with a modulating boiler if simulated with reference year M2, while, if the other reference years are used, the optimum can be achieved with a condensing boiler. As regards the optimal insulation, a greater variability is found, especially for the configurations with South-oriented windows. As a whole, the uncertainty in the *NPV* of the cost-optimal solutions ranges between 1000 and

3000 €, increasing when building configurations with larger S/V and energy demands are considered.

Energy optimal

The energy optimal configurations present slight differences in terms of ESM_s especially in East-oriented cases, but have different EP_h because of the different weather file used (Tables 4 and 5). The insulation thickness is generally equal or close to the maximum allowable (i.e., 20 cm) with the exception of the building with $S/V = 0.3 \text{ m}^{-1}$ and South-oriented windows, whose optimal insulation ranges from 13 cm (reference years M1, M4 and M6) to 18 cm (reference year M3). The original windows are almost always changed with triple-pane glazing

systems: they have always high $SHGC$, excluding the intermediate flats with windows on the South façade, for which triple glazing with low $SHGC$ are preferred for all reference years except M1, and the semi-detached house with South-oriented windows, for which double glazing with high $SHGC$ is the best solution with reference year M6.

Mechanical ventilation system is always adopted, independently of the reference year. As regards the boiler, the condensing one is the prevalent optimal solution but for the building with $S/V = 0.3 \text{ m}^{-1}$ and East-oriented windows, if reference year is M2 or M3, no replacement is suggested.

Table 4

$EP_h [kWh \text{ m}^{-2} \text{ yr}^{-1}]$ and $NPV [k€]$ for the building configurations with East-oriented windows according to the six reference years: characteristics of energy and cost-optima

East	$S/V = 0.3 \text{ m}^{-1}$						$S/V = 0.63 \text{ m}^{-1}$						$S/V = 0.97 \text{ m}^{-1}$					
	M1	M2	M3	M4	M5	M6	M1	M2	M3	M4	M5	M6	M1	M2	M3	M4	M5	M6
Energy-Optimal																		
Wall	20	20	20	20	20	20	20	19	19	19	19	20	20	19	18	19	18	18
Roof	0	0	0	0	0	0	19	19	19	20	20	20	20	19	19	19	19	19
Floor	0	0	0	0	0	0	0	0	0	0	0	0	20	20	20	20	19	19
Wind.	TH	TH	TH	TH	TH	TH	TH	TH	TH	TH	TH	TH	TH	TH	TH	TH	TH	TH
Boiler	COND	STD	STD	COND	COND	COND	COND	COND	COND	COND	COND	COND	COND	COND	COND	COND	COND	COND
Vent.	MVS	MVS	MVS	MVS	MVS	MVS	MVS	MVS	MVS	MVS	MVS	MVS	MVS	MVS	MVS	MVS	MVS	MVS
EP_H	0.55	0.73	0.62	0.93	0.93	0.89	15.39	12.08	15.35	12.87	14.01	13.68	27.84	23.43	28.69	26.17	29.20	29.13
NPV	30.74	27.91	27.88	30.84	30.84	30.83	39.61	38.57	39.47	39.00	39.31	39.35	48.24	46.70	48.00	47.45	47.93	47.91
Cost-Optimal																		
Wall	19	17	18	19	19	18	18	18	17	17	17	17	19	18	17	18	16	18
Roof	0	0	0	0	0	0	17	19	17	17	17	17	19	17	18	18	17	18
Floor	0	0	0	0	0	0	0	0	0	0	0	0	18	18	18	18	17	19
Wind.	DH	DH	TH	DH	DH	DH	DH	DH	DH	DH	DH	DH	DH	DH	DH	DH	DH	DH
Boiler	STD	STD	STD	STD	STD	STD	COND	MOD	COND	COND	COND	COND	MOD	COND	COND	COND	COND	COND
Vent.	NAT	NAT	NAT	NAT	NAT	NAT	NAT	NAT	NAT	NAT	NAT	NAT	NAT	NAT	NAT	NAT	NAT	NAT
EP_H	27.23	23.23	23.27	24.62	25.84	26.48	38.27	34.59	38.60	36.24	38.03	37.91	55.09	46.87	51.46	48.56	52.93	49.80
NPV	20.23	18.88	20.18	19.52	19.85	19.89	30.40	28.92	30.35	29.71	30.20	30.16	39.26	37.36	38.68	38.03	38.54	38.57

Table 5

$EP_h [kWh \text{ m}^{-2} \text{ yr}^{-1}]$ and $NPV [k€]$ for the building configurations with South-oriented windows according to the six reference years: characteristics of energy and cost-optima

South	$S/V = 0.3 \text{ m}^{-1}$						$S/V = 0.63 \text{ m}^{-1}$						$S/V = 0.97 \text{ m}^{-1}$					
	M1	M2	M3	M4	M5	M6	M1	M2	M3	M4	M5	M6	M1	M2	M3	M4	M5	M6
Energy-Optimal																		
Wall	13	16	18	13	14	13	20	20	20	20	20	20	19	19	19	18	18	18
Roof	0	0	0	0	0	0	20	20	20	20	20	20	19	19	19	17	19	19
Floor	0	0	0	0	0	0	0	0	0	0	0	0	18	18	20	18	20	16
Wind.	TH	TL	TL	TL	TL	TL	TH	TH	TH	TH	TH	TH	TH	TH	TH	TH	TH	DH
Boiler	COND	COND	COND	COND	COND	COND	COND	COND	COND	COND	COND	COND	COND	COND	COND	COND	COND	COND
Vent.	MVS	MVS	MVS	MVS	MVS	MVS	MVS	MVS	MVS	MVS	MVS	MVS	MVS	MVS	MVS	MVS	MVS	MVS
EP_H	0.54	0.52	0.54	0.53	0.52	0.51	1.42	1.01	1.54	1.36	1.33	1.30	11.23	8.21	11.88	10.93	10.56	13.69
NPV	29.81	29.83	30.10	29.43	29.57	29.43	36.01	35.90	36.04	36.00	35.99	35.98	42.97	42.14	43.56	42.34	43.06	41.93
Cost-Optimal																		
Wall	17	15	17	14	18	18	17	16	18	17	17	17	17	18	17	17	17	17
Roof	0	0	0	0	0	0	15	17	16	18	16	16	18	16	18	17	17	17
Floor	0	0	0	0	0	0	0	0	0	0	0	0	17	17	16	16	18	16
Wind.	DH	DH	DH	DH	DH	DH	DH	DH	DH	DH	DH	DH	DH	DH	DH	DH	DH	DH
Boiler	STD	STD	STD	STD	STD	STD	STD	STD	STD	STD	STD	STD	MOD	MOD	MOD	MOD	MOD	MOD
Vent.	NAT	NAT	NAT	NAT	NAT	NAT	NAT	NAT	NAT	NAT	NAT	NAT	NAT	NAT	NAT	NAT	NAT	NAT
EP_H	8.02	5.92	9.39	7.76	6.83	6.81	25.78	19.21	26.71	19.13	22.97	22.95	33.61	27.15	36.25	30.48	30.99	32.96
NPV	14.73	13.90	15.11	14.26	14.54	14.54	23.57	22.06	24.17	22.38	23.01	23.01	32.73	30.69	33.24	31.46	32.02	32.14

Considering the uncertainty in the EP_h of the energy-optimal solutions, it is almost null for the most compact buildings and about $5 \text{ kWh m}^{-2} \text{ yr}^{-1}$ for those with the highest S/V .

CONCLUSION

In this work, the robustness of a genetic algorithm, the Elitist Non-dominated Sorting Genetic Algorithm, was assessed in the framework of multi-objective optimizations of building energy refurbishment through building energy simulation. In particular, the focus was on the issues due to suboptimal hourly weather data and on the impact of the method for the development of reference years. Six reference years implementing just as many different methods were developed for the location of Trento, north Italy. These reference years were used as inputs for the refurbishment multi-objective optimization of six buildings with three ratios between the externally exposed surface and the conditioned volume and two alternatives of windows orientations. Among the available energy saving measures for the reduction of final uses for space heating, wall insulation, windows and boiler substitutions and installation of a mechanical ventilation system with heat recovery were considered. The optimization involved the trade-off between primary energy for space heating and net present value of the investment, which were studied in terms of Pareto fronts.

Since each reference year gave specific initial conditions of EP_h and NPV , different Pareto fronts were found for each building configuration. However, the results showed that fronts are not simply shifted on the $NPV-EP_h$ chart but, in some cases, they can have different shapes and propose different optimal solutions.

The actual choice of the optimal ESM in Pareto front depends on the weights given to the objectives in trade-off. In order to analyse which $ESMs$ are more sensitive to the weather data input, two separate studies were performed to look for (a) the ESM optimizing the NPV and (b) the one optimizing the EP_h among those on Pareto fronts. According to the building kind, different sensitivities were found but, in general, the insulation level and the boiler replacement presented the largest variability, which was more emphasized in the NPV optimization context. The selection of the best solution for window substitution demonstrated to be, to some extent, more robust to the weather inputs. As regards the ventilation, no sensitivity at all was detected for the considered buildings.

The results of this study confirmed the findings found in previous works (Prada *et al.*, 2014) about weather inputs, allowing us to conclude that if some representativeness issues are present in the reference years – because of either the methodology for the reference year definition or the inadequacy of the historic multi-year weather data series, different

optimal $ESMs$ can be identified through the multi-objective optimization.

NOMENCLATURE

A	= surface (m^2)
BES	= building energy simulation
c	= specific heat ($J \text{ kg}^{-1} \text{ K}^{-1}$)
d	= thickness (m)
$COND$	= condensing boiler
D	= double glazings
EP	= primary energy ($\text{kWh m}^{-2} \text{ yr}^{-1}$)
ESM	= energy saving measure
FS	= Finkelstein–Schafer statistic
H	= high $SHGC$
HDD	= heating degree days ($K \text{ d}$)
GA	= genetic algorithm
I	= solar irradiation ($\text{MJ m}^{-2} \text{ d}^{-1}$)
λ	= thermal conductivity ($\text{W m}^{-1} \text{ K}^{-1}$)
L	= low $SHGC$
κ	= thermal capacitance ($\text{kJ m}^{-2} \text{ K}^{-1}$)
MOD	= modulating boiler
MVS	= mechanical ventilation
NAT	= natural ventilation
NPV	= net present value (€)
R	= thermal resistance ($\text{m}^2 \text{ K W}^{-1}$)
ρ	= specific mass (kg m^{-3})
S	= envelope exposed surface (m^2)
$SHGC$	= solar heat gain coefficient (-)
STD	= standard boiler
T	= triple glazings
U	= thermal transmittance ($\text{W m}^{-2} \text{ K}^{-1}$)
V	= conditioned volume (m^3)
Subscript	
fr	= frame
gl	= glazing
h	= heating
sol	= solar
win	= window

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