Title: A systematic review of Genetic Algorithm-based Multi-Objective Optimisation for building retrofitting strategies towards energy efficiency

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Abstract

Most common practices for solving building retrofit problems lack efficiency and overall robustness. Knowledge of novel methods that support decision-making (DM) for retrofitting is critical for sustainability and energy performance improvement. This systematic review for the first time provides a large evidence-base to assess the potential of Multi-objective optimisation (MOO) using Genetic algorithm (GA) for supporting the development of retrofitting strategies and its DM process. From 557 screened studies, 57 were reviewed focusing on outcomes, current trends, and the method's potential, challenges, and limitations.

Key findings reveal a strong suitability for solving a wide range of building retrofit MOO problems, based on robust outcomes with significant objectives improvement. However, results also indicate that yielding optimal retrofit solutions may require GA-mixed techniques or modified GA, due to time-consuming and effectiveness issues. Heritage buildings, where qualitative objective function definition is particularly challenging, have been little addressed. Further challenges include: lack of standard systematic approach; complex switch between modelling and optimisation environment; high expertise needed to perform MOO and manage software; and lack of confidence in results. While GA-based MOO's robust evaluation for supporting building retrofit and its DM process needs further research, promising potential is shown overall, when complemented with auxiliary techniques.

Keywords: systematic review, multi-objective, optimization, genetic algorithms, retrofit
[1]

Abbreviations: AB: Archetype Building; AHP: Analytic Hierarchy Method; AM: Aggregating methods; ANN: Artificial Neural Network; BEOT: Building Energy Optimisation Tool; GA: Genetic Algorithm; BPO: Building Performance Optimisation; BPS: Building Performance Simulation; DM: Decision-making; ERM: Energy retrofit measures; HVAC: Heating, Ventilation and air conditioning; IEQ: Indoor Environment Quality; IR: Interested Reader; Isum: Summer Comfort Index; LHS: Latin Hypercube sampling; MOEA: Multi-objective Evolutionary Algorithms; MOGA: Multi-objective Genetic Algorithm; MOO: Multi-objective optimisation; NSGA: Non-dominated Sorting Genetic Algorithm; NSGA-II: Elitist Non-dominated Sorting Genetic Algorithm; PMV: Predicted Man Vote Index; PPD: Predicted Percentage of Dissatisfied; PS: Primary Studies; PV: Photovoltaic; RB: Real Buildings; RSA: Response Surface Approximation Model; SA: Sensitivity analysis; SBM: Simplified Building Model; SPEA: Strength Pareto Evolutionary Algorithm; SR: Systematic Review; SSS: Sobol sequence sampling; VEGA: Vector evaluated genetic algorithm; WSM: Weighted Sum Method; ZOGP: Zero-One Goal Programing.

1. Introduction

In building design and retrofit problems, computational optimisation involves firstly simulation and analysis, before undertaking a search process to determine an optimal design solution or set of solutions from a wide range of feasible options, according to the objective and restriction functions defined [1–3]. The number of objective functions to be maximised or minimised, primarily defines the nature of the optimisation problem: mono-objective optimisation targets one objective, while multi-objective optimisation (MOO) targets two or more objectives to be optimised simultaneously [4].

In particular, MOO has been receiving growing interest from both research and industry sectors in recent years [3,5–7], due to offering a more accurate portrait of the real-world decision-making (DM) than approaches achieving a single solution, while providing the flexibility of choosing amongst a set of solutions after understanding what is at stake through trade-off analysis. In parallel, building retrofitting has been gaining ground, representing nearly half of the construction sector in developed countries [8]. Even though optimisation is becoming a more frequent approach in new construction, its role in retrofit projects has been largely overlooked [9–11]. According to Attia et al. [4], retrofit accounts for as little as 7% within MOO in the building sector. Yet, a major opportunity for improving energy efficiency and sustainability lies in building retrofitting [12]; this sector is multi-objective by nature and entails managing several conflicting goals under a considerable level of uncertainty due to many variables [8,13]. In addition, most techniques being used as common practice for solving building retrofit problems lack efficiency and overall robustness [14].

It is therefore essential to develop and incorporate innovative methodologies that aid the decision-making (DM) process and allow exploring the design space for alternative solutions in an efficient and effective way, contributing to the increase of energy efficiency and overall performance in retrofitted buildings. In this regard, evolutionary multi-objective optimisation (EMO) methods, such as genetic algorithms (GAs), could provide a powerful tool for DM in building retrofit. In fact, evolutionary methods have been occupying a dominant position in real-world MOO problem-solving for the past decade [15,16], but are in their early beginnings where retrofit optimisation problems are concerned, as their popularity started to rise mostly in the past couple of years. Thus, an up-to-date systematic review (SR) of GA-based MOO applied to building retrofitting is relevant and needed to help fill in this current gap.

1.1. Overview of existing reviews

Due to the growing interest in the integration of optimisation into the building design process, several reviews have been undertaken in recent years focusing on optimisation in the general sense. Yet, the core literature on

GA-based MOO, as a tool for the decision-maker in building retrofit, has not been, to the authors' knowledge, previously fully covered and analysed. Key existing reviews and studies touching on the topics of GA and MOO are summarised hereunder.

A review of the existing retrofit decision support tools was developed from the user's perspective, following a life cycle approach classification [17]. It included 9 publications on GA, from which only 4 use a MOO GA-based method applied to building retrofitting. Focusing on sustainable building design, Evins et al. [5] provided a comprehensive review of computational optimisation methods, including mono-objective and MOO and several optimisation methods, amongst which GA, stratified in three main fields of building design: building envelope, systems, and renewable energy generation. A short separate section specifically looking at retrofit cases is presented. Its conclusions highlight the wide span of optimisation approaches applied in sustainable building design. Also in 2013, Asadi et al. [18] tackled a state of the art review of retrofit strategies entailing optimisation and GA, before the topic escalated from 2014 onwards. Its approach differs from that of this SR as it focused on retrofit assessment methodologies, discussing both advantages and drawbacks of Multi-Criteria Decision Analysis (alternatives are explicitly known a priori) and Multi-objective programming (alternatives are implicitly defined by an optimisation model) approaches. Nguyen et al. [3] reviewed the efficiency and challenges of building MOO simulation-based optimisation methods and the issues with integrating optimisation methods into building performance simulation and conventional design tools. Attia et al. [4] also explored the challenges and opportunities of the integration of building performance optimisation (BPO) in the building design process specifically looking into net zero buildings, with a mixed-method research based on literature analysis and optimisation experts' interviews. GA was covered amid a section on algorithms used in BPO and mono-objective and multi-objective functions are presented. Low trust in results, mainly due to lack of awareness in practice, lack of a standard systematic approach to perform optimisation which results in many different methods and unstructured approaches, and requirement of a high level of expertise are listed amongst the identified optimisation shortcomings. Machairas et al. [7] developed a survey on optimisation algorithms and tools in building design and suggested possible further developments as to the incorporation of optimisation methods into the building design process. In [6], Shi et al. collected and analysed 116 research papers on building energy efficiency design optimisation, focusing on architects' perspective. The analysis covered optimisation techniques' classification, objectives and design variables, energy simulation engines, optimisation algorithms including evolutionary, derivative-free search and hybrid algorithms, the overall state of building energy efficient design optimisation techniques, what is missing for architects and future work suggestions. Additionally, Longo et al. [19] provided the most recent review on optimisation of low-energy buildings design, with a special focus on Net and Nearly Zero-Energy Buildings. It compared and analysed different methodologies, optimisation algorithms, variables, objectives, and software, confirming the growing research interest in building retrofit, amounting to 31 studies collected. In addition, its conclusions emphasised that, as a result of the immense diversity of approaches followed by the scientific community, it was not possible to identify a common frame of investigation; nevertheless, MOO and GA, NSGA-II in particular, were highlighted as most popular amongst other methods and techniques.

Finally, several studies, while not reviews, did include tabulated overviews of: recent simulation and/or mono-objective and MOO literature on building retrofit, based on several methods and encompassing 16 studies [20]; 16 studies related to energy-efficiency DM for building retrofitting, inclusive of both mono-objective and MOO, amid other methods, techniques and algorithms [21]; 24 MOO studies applied to building energy retrofitting using different optimisation algorithms and compared against each other [22]; 20 mono-objective and MOO building retrofit optimisation studies, showcasing the type of building and construction date, along with a diversity of optimisation methods, objective functions and energy use evaluation information [23]; a five-year timespan literature review concerning building design and energy retrofit optimisation, and covering the use of several types of optimisation algorithms [24].

On a final note, three other reviews of note included: a significant survey on GA-based MOO techniques and their classification [25]; the analysis of computational optimisation methods applied to renewable and sustainable energy [26]; and a comprehensive review of the most popular data-driven approaches, their classification and applications to predict building energy consumption, including GA in building retrofit projects and MOO [27].

1.2. Goals of this review and research questions

For GA-based MOO to be absorbed into DM processes in building retrofit, more knowledge is needed on its main features, development, performance and current implementation challenges. Hence, the goal of this study is to address the existing gap by offering an updated and comprehensive SR on GA-based MOO applied to building retrofit problems, as a tool for the decision-maker. Furthermore, the major driving force behind this SR is the intention to establish a common knowledge platform to boost further work on this topic, by collecting, analysing, summarising and comparing key outcomes obtained thus far and revealing its challenges and limitations. In doing so, the following research question is addressed:

- What is the potential of GA-based MOO in supporting the development of retrofitting strategies and the decision-making process?

In order to answer it, the following objectives are set to investigate:

- How is GA-based MOO being applied in building retrofit? Which techniques aid its implementation and what type of case studies are being covered;
- Which are the current trends regarding the objective functions explored for optimal trade-offs, as well as the decision variables chosen for optimisation;
- Which type of simulation-optimisation approach and software tools can be identified as preeminent in GA-based MOO;
- What types of outcomes are being achieved; whether retrofit solutions obtained are robust and how does it impact the optimisation performance time;
- What major challenges and limitations can be pinpointed in the implementation and outcomes of GA-based MOO in building retrofit, and which thorough techniques have proven successful in overcoming them;
- Whether traditional and heritage buildings are being targeted in GA-based MOO retrofit studies, and if so, which objective functions are being addressed; Which methods and techniques are being used to quantify heritage qualitative concepts such as conservation compatibility.

To achieve these objectives, this paper is divided into four sections: the first provides the methodological framework for the search strategy, inclusion and exclusion criteria definition and selection method. Afterwards, a background on MOO and the key features of GA are presented, in order to establish a common understanding regarding fundamental concepts and associated terminology. The third section presents the data extraction in tabulated form and its analysis, according to the following subsections: case study characteristics; optimisation methods and techniques employed; objective functions and decision variables optimised; simulation-optimisation approach and tools used and historical, traditional and special architecture value buildings. Finally, a discussion of the main findings, outcomes, and potential of the method, challenges and limitations is undertaken. Gaps in the available literature and future research needs are identified, and the strengths and limitations of the study are examined.

2. Methodology

The methodology adopted in the present SR is based on the PRISMA statement approach [28].

2.1. Search strategy

The search strategy developed entailed a database search, blind to impact factor, coupled with a citation snowballing approach and a citation pearl growing strategy. The initial information sources comprised two main academic literature collections: Web of Science (WOS), including Web of Science Core Collection, and Scopus databases [29]. The iterative databases search was performed using keywords to identify key academic literature and the last search took place on August 27th, 2019. The key terms were searched for with no timespan limit, in the topic and title (WOS) and topic, title and abstract (Scopus). The document type was limited to: article, review, proceedings paper, bibliography (WOS) and article and conference paper, article or review (Scopus). All languages and access type options were selected. The keywords, Boolean, truncation (asterisk (*) operator providing search with terms alternate endings) and proximity operators (Within (W/n) in Scopus and Near (Near/x) in WOS) used are listed in table 1. Additionally, different keywords spellings were searched. This amounted to 466 records.

Table 1
Search strategy keywords.

	Keywords
1	*Genetic algorithm Building retrofit*
2	“*Multi-objective optimization” AND “genetic algorithm*” AND “*Building retrofit”*
3	“optimiz*” AND “*“genetic algorithm*” AND “building *retrofit*”*
4	“*Multi-objective optimization building retrofit” AND “genetic algorithm*”
5	Multi-objective W/1 optimization W/5 building retrofit
6	Multi-objective W/1 optimization W/5 building retrofit AND genetic algorithm
7	TS=(Multi-objective optimisation AND genetic algorithm AND building retrofit)
8	TS=(“optimiz*” AND “genetic algorithm” AND “building retrofit”)
9	TS=(Multi-objective NEAR/1 optimization NEAR/5 building retrofit)
10	TS=(Multi-objective NEAR/1 optimization NEAR/5 building retrofit AND genetic algorithm)
11	TS=(multi-objective NEAR/1 optimiz* NEAR/5 building retrofit*)
12	TI=(Multi-objective NEAR/1 optimization NEAR/5 building retrofit)

A citation snowballing approach [30] further expanded the search strategy. Backward snowballing was undertaken by scanning reference lists for relevant papers, retrieving them, scanning their own reference lists and so on, until the exhaustion of relevant references was achieved. Forward snowballing was additionally developed based on cited reference searching, to find more contemporary publications that have cited the starting point publication. The implementation of this strategy contributed to further 74 potentially relevant records.

Since Scopus and WOS do not use a controlled vocabulary, a citation pearl growing strategy was particularly useful to complement the search range of terms that make reference to the topic of the review, based on new search terms found in titles, abstracts, and keywords. These included keywords synonyms, narrower terms and verbal and noun forms (Table 2), which resulted in 17 extra records.

Table 2
Keyword expansion.

	Keywords synonyms, narrower terms, verbal/noun forms and other optimisation related expressions
1	Multi-objective optimization – *Multi-variable opt.; multicriteria opt.; multi-dimensional Pareto opt.; simultaneous opt.; evolutionary multi-objective opt.; multiple objective decision; multi-criteria decision making; automatic generation of multiple retrofitting measures; simultaneous minimiz*/maximiz*; decision support system*
2	Optimal trade-off; optimal retrofit solutions/options/measures/actions/decision; cost-optimal*
3	Existence/reference building/building envelope retrofit – *Refurbishment; upgrade; renovation; reconstruction; renewal; improvement; maximising sustainability*
4	Energy efficiency upgrade/retrofit/performance improvement/saving measures/retrofit strategies
5	Genetic algorithm (GA) - *Multi-criterion GA, Pareto GA, Multi-objective evolutionary algorithm, multi-objective*
6	GA; two-objective GA; NSGA-II
7	Pareto optimization; Pareto front; Pareto optimal solutions; weighted sum method
8	Objective functions; decision variables; constraints

2.2. Inclusion and exclusion criteria definition

The authors developed inclusion and exclusion objective criteria related to the characteristics of the publications, such as research scope, optimisation topic, time frame, geographic context, language, optimisation techniques, and scientific quality standards. The definition and justification of these criteria are summarised in Table 3.

Table 3
Inclusion and exclusion criteria definition.

	Criteria	Range	Justification
Inclusion criteria	**Research scope**	GA-based MOO implementation process in energy efficient building retrofit	Range directly relevant to review goals
	Optimisation topic	Envelope, building systems (mechanical, energy, control), renewables and form	Range directly relevant to energy efficient retrofit and the whole building performance
	Time frame	No time frame limit	No time frame was set, yet no relevant publications prior to 2000 were obtained
	Geog. Context	Worldwide	A global state-of-the-art requires unlimited geographic context

	Language	English-language publications	No language restrictions were imposed in the searching strategy, however only english-language records were obtained
	Scientific Quality standards	Published research and full-article publications	Required for the studies selection process
		Peer-reviewed in sci. Journals and conf. proc.	Research with established validity
		Blind to impact factor	Not relevant to review goals
	Opt. Techniques	Algebraic and computational	Allowing for a comparison of different implementation methods
Exclusion criteria	**Research scope**	MOO in building retrofit with other Evolutionary algorithms (e.g. PSO, HS, HJ, Nelder and Mead simplex, PSO-HJ)	Off-topic. The interested reader is referred to: [23,31–39]
		MOO in building retrofit with other Opt. methods	Off-topic. The IR is referred to: [40–48]
		Mono-objective opt. using GA in building retrofit	Off-topic. The IR is referred to: [41,49] (energy cons.), [50–52] (environmental impacts), (thermal comfort) [53], [21,49,54] (Cost), [55] (productive time)
		GA- based MOO in building design	Off-topic. Covered in previous reviews covering global optimisation methods [4–6,56];
	Optimisation Topic	Seismic retrofit using MOO with GA	Off-topic. The IR is referred to: [57–61]
		Energy facilities retrofit with GA-MOO (e.g. Hybrid power plant coal power station, wind turbine)	No link to building performance
		Structure and infrastructures GA-MOO with GA (e.g. Steel-moment resisting frames, two dimensional structures, bridges, water network)	No link to whole building performance
		Building systems retrofit not linked to the whole build. performance (e.g. Heat exchanger, solar chimney)	No link to whole building performance
		Decision variables unrelated to building retrofit components	Off-topic. The IR is referred to: [62] (investment/capital decision variables)
	Scientific quality standards	Grey literature	
		Duplicate records and research	Overlapping publications between databases Overlapping research between peer-reviewed papers and conference proc.

2.3. Studies selection method

The method followed for the primary studies (PS) selection is structured into four stages: identification; two-level screening; eligibility; inclusion [28] (fig.1).

The first stage identifies all potentially relevant studies, adding up to 557 studies. 59 duplicate studies and research were excluded from this number. This included both overlapping studies between databases as well as overlapping research between peer-reviewed papers and conference proceedings (e.g. [63–65]).

The second stage conducts a preliminary assessment through title, keywords and abstract screening. At this stage, 413 records are excluded for not meeting inclusion criteria, in particular regarding the research scope and optimisation topic. Both records tagged as include and those unclear were passed on to further assessment. A more detailed evaluation is conducted by means of methodology and conclusions screening, discarding 7 more records. 78 records access the third stage, where the eligibility of the studies is analysed through careful full-text review. Finally, out of the 78 full-text records reviewed, 57 met the inclusion criteria in their entirety and were included in the SR.

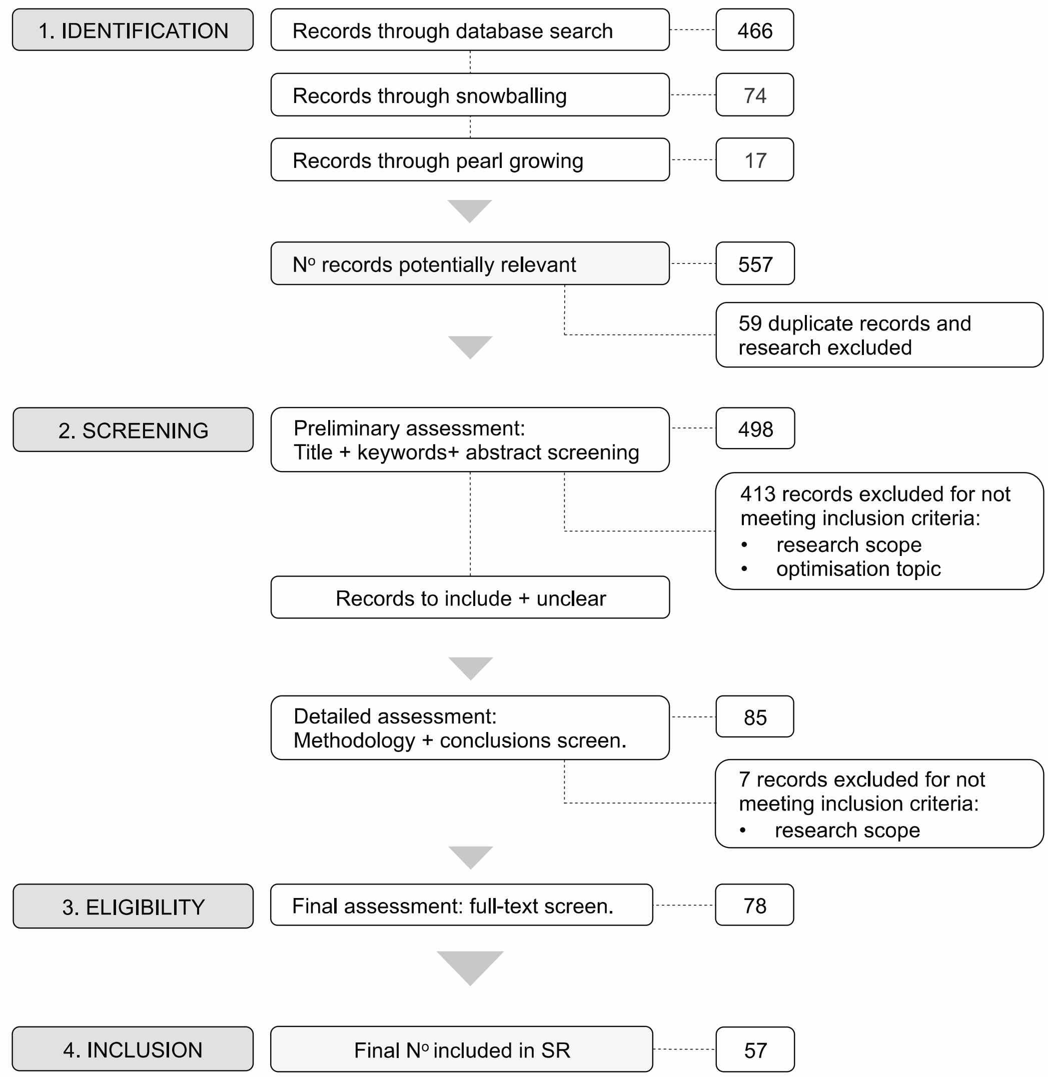

Figure 1. Primary studies selection process flowchart.

3. Multi-Objective Optimisation

In the building retrofit sector, the DM process entails a trade-off relationship of sacrifice and gain between two or more objectives that can be optimised. The generally conflicting nature of the simultaneous optimisation of these objectives, such as minimising the retrofit cost while maximising energy savings and indoor thermal comfort, defines a MOO problem.

In a MOO problem, there is a set of solutions, rather than a mono solution, that can be used for trade-off analysis. This approach offers a more accurate portrait of the DM process than approaches achieving a mono solution. The objectives are the function of another set of parameters, the decision variables, which are the variables you can control within the optimisation model (e.g. retrofit measures). The solutions are not known a priori, however, they are determined by the definition of constraints delimiting the optimisation search space, as they represent the conditions that must be met.

Conventional optimisation search methods, i.e. non-evolutionary-based methods, have been common practice for DM in building retrofit to date, due to their relative simplicity. Nonetheless, their basic design features inhibit their application in MOO problems [66]**.** Additionally, they present several drawbacks: expert knowledge-based optimisation is limited by its use of best construction practice, generally coupled with dynamic energy simulation, to achieve a series of recommendations through iterative procedure [3,67–69]; scenario-by-scenario or trial-and-error simulation evaluation, where a solution is generated and subsequently simulated for evaluation, results in a limited number of retrofit options being assessed, with no guarantee to achieve optimal solutions [18,43,70,71]; or the time-consuming brute-force, which employs an exhaustive search to sample the whole solution space [2,72,73]. Simulation-based parametric approaches have been less commonly used in building retrofit practice for its requirement of powerful resources to simulate an extended number of potential solutions [65,74]. Additionally, Sensitivity analysis (SA) approaches have also been applied as auxiliary techniques in the optimisation process. They allow for the identification of the most influential building parameters associated with performance and hence facilitate an optimisation centred on those results [75,76].

However, various strategies can be implemented to successfully solve MOO problems, amongst which, aggregating methods (Weight sum approach; Goal programming-based approach; Goal attainment-based approach; ε-constraint approach) and Pareto-base strategies (Pareto-based elitist strategies, e.g. Strength Pareto Evolutionary Algorithm (SPEA); SPEA2; Elitist Non-dominated Sorting Genetic Algorithm (NSGA-II); Pareto-based non-elitist strategies, e.g. Multi-objective GA (MOGA); Niched Pareto GA; Non-dominated sorting GA (NSGA)) are the most resorted to [25,66,77]. The following paragraphs describe the key concept and techniques of both methods in more detail, as follows:

- AM resolve MOO problems by reformulating them as mono-objective ones. The following are some approaches of AM:
    - The weighted sum approach, which is particularly popular due to its straightforwardness: each objective function is normalised and summed up with their assigned weights [3,15,26,78–80]. Some of its drawbacks are tied to the weight factors adjustment accuracy, the restricted DM process as a result of the narrowing down to a mono solution process and an increase in processing time for testing different weight factors [79,81].
    - The ε-constraint approach, which optimises one of the objective functions by defining all other objective functions as constraints. This also entails arbitrariness linked to the constraining value assignment;

- The Pareto-based optimisation concept, first introduced in building design in the 1980s by Radford, Gero and D'Cruz [82–86], relies on the identification of a set of all feasible solutions (building design or retrofit options), which is Pareto-optimal or non-dominated (fig 2). Being non-dominated implies that no solution within it can improve an objective without being detrimental to at least another one [87,88]. Said set of solutions constitutes the Pareto front, which represents the optimal trade-off between the objectives considered in the analysis [7,15,89]. This concept is illustrated in fig 2, where A and B represent non-dominated solutions and both individually dominate C. Among the Pareto-based strategies, population-based GA is systematically crowned as the leading method used to solve building optimisation problems [3,5,15,26,67].

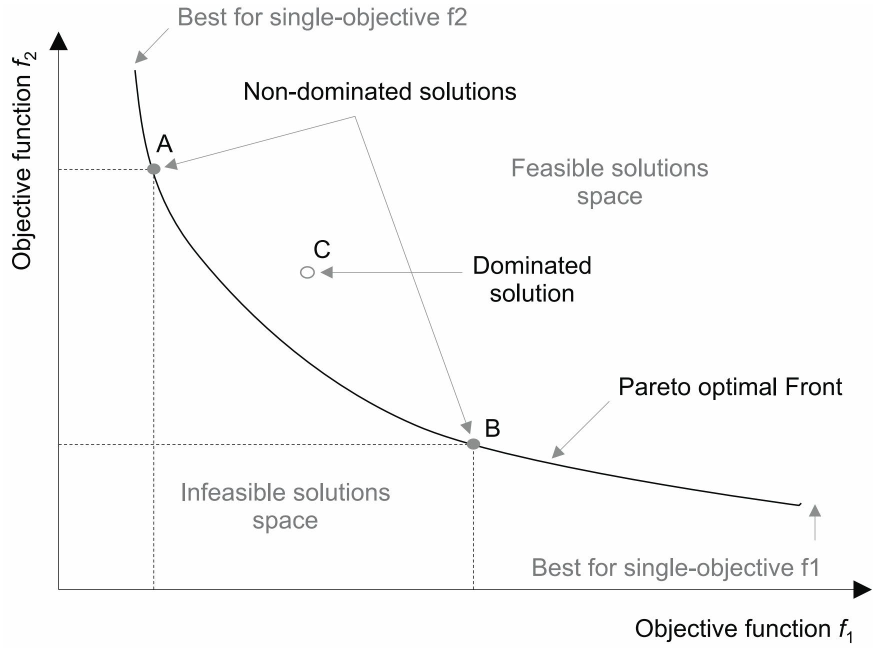

Figure 2. Pareto-based optimisation concept illustration for a two-objective problem.

4. Genetic Algorithm in Multi-objective optimisation

The implementation of multi-objective GA was introduced in the mid-1980s by Schaffer [90], with the VEGA mainly aiming at solving problems in machine learning. Since then, several other algorithms have been developed which can differ in their fitness assignment, elitism and diversification processes. Several comparative performance reviews have been developed. The interested reader can refer to: [49,81,91,92] comparing multi-objective GA algorithms performance with other multi-objective evolutionary algorithms (MOEA); [15,49,93] examining GA and other meta-heuristic methods; [7,94–96] addressing GA and other building design optimisation algorithms; [97–99] contrasting stand-alone GA and GA-based hybrids or modified GA.

GAs' performance has been tested in a myriad of reviews and comparative studies, and the literature overwhelmingly suggests that GAs have been the most popular and robust heuristic approach to MOO problems in the field of building optimisation [3,4,27,62,93,100–106,5,107–111,6,7,15,18,19,22,23]. Its concept, developed by Holland [112] in the 1960s and 1970s, consists in a stochastic population-based search algorithm that generates solutions for optimisation problems, based on the mechanics of natural selection and genetic operators [14,65,69,101,113]. In fact, GAs principles are modelled on Darwin's evolutionist theory of the survival of the fittest and natural selection mechanisms [114], where organisms gradually self-modify to produce generations that better adapt to their environment and become dominant in their population [14]. The random choice tool adopted by this class of algorithms to guide a highly exploitative search through coding of parameter space [14], has always been found in nature, where beneficial random gene changes allow for new species to evolve from older ones, while unfavourable changes are eliminated by natural selection.

In GA terminology, a solution vector is called an individual or a chromosome, which is made of a set of parameters called genes (decision variables). A chromosome normally represents a unique potential solution in the solution space. The first step in simple GA implementation consists of the encoding of the problem, which refers to the mapping mechanism between the solution space and the chromosomes. GA then randomly generates the initial population of chromosomes, which matches the set of potential solution points. A competitive evaluating mechanism is applied to each chromosome during the reproduction process, established on the survival of the fittest principle; in practice, the evaluation of the fitness function for each individual, i.e. its fitness value or how close it is to the targeted objective function, determines its probability of being selected and copied into the next generation of chromosomes: the offspring. Hence, inferior solutions are discarded in each generation, resulting in generations of increasingly fitter solutions while maintaining population size. Genetic operators manipulate the selected chromosomes, to generate new offspring. Those frequently used are: selection, crossover, and mutation. The selection makes reference to the copying of individual strings from the parent chromosomes into the new population. The most commonly employed individuals selection method is the tournament selection, where a number of individuals are randomly chosen from the population, compared with each other and the best is chosen to be a parent, followed by fitness-proportionate selection [115]. Then GA applies the crossover operator, which is the most important genetic-mimicking probabilistic operator and combines two high fitness parent solutions, or partial string exchanges, to create a new generation solution. Population diversity is guaranteed by the mechanism of mutation, which acts secondarily to crossover as an insurance against the loss of genetic material that can occur with the first two procedures. It works by occasionally and randomly modifying the value of one or more bits of offspring and consequently introducing new genetic material. Additionally, the elitism operator can be adopted by randomly replacing one chromosome of the current population with the chromosome with maximum fitness value from the previous generation [66,89]. Finally, if one or more pre-specified stopping criteria are met, the generation process comes to an end. Otherwise it restarts at the crossover stage [14,15,69,78,116]. These stopping criteria most often include [14,66,89,112,115]:

- Maximum number of generations: GA stops after the maximum number of iterations that it is set to run for;
- Fitness limit: GA stops when the value of the fitness function for the best point in the current population is less than or equal to the fitness limit defined;
- Stall time limit and stall generations limit: GA stops if there is no improvement in the best fitness value for a predefined interval of time in seconds or predefined number of generations;
- Objective function value: GA stops as soon as a desired objective function value is attained by at least one string in the population;
- Time limit: GA stops after running for a maximum time in seconds. The time limit is enforced after each iteration which allows GA to exceed it when an iteration takes substantial time;
- Convergence: GA stops after convergence, i.e. progression towards increasing uniformity. In other words, population convergence entails evolution over successive generations so that the fitness of the best and the average individual in each generation increases towards global optimum.

At the end of the process, a set of possible alternative solutions is obtained, which is particularly interesting for a MOO scenario [66].

GAs' popularity can, in fact, be attributed to an assortment of well known characteristics that distinguish them from conventional optimisation methods [14], contribute to their robustness and make them especially well-suited for the conflictive nature of multiple-objective problems and convergence on the Pareto optimal set as a whole [3,15,60,78,100]:

- GAs work directly with the parameter set coding, instead of the parameters themselves;
- GAs search from a population of points, not from a mono point; GAs handle a large number of local minimums and maximums;
- GAs provide an efficient set of multiple solutions: GAs are not guaranteed to find global optima but the solutions yielded represent significant improvement;
- GAs are less likely to converge to a local minimum;
- GAs are blind to auxiliary information: they use objective function values only;

- GAs use probabilistic transition rules to guide their search, not deterministic rules: GAs use random choice (randomised operators) as a tool to guide a search toward regions of the search space with likely improvement;
- Most GAs do not require the use of prioritising, scaling or weighing objectives;
- GAs efficiently handle non-linear problems with discontinuities.

In addition to the aforementioned features, GA extensive use in building optimisation is repeatedly attributed to: its ability to work with a population of individuals that expectedly converges to the true non-dominated Pareto front [18,77,89,117]; its flexibility and robust performance as a search method without exhausting the entire search space [18,23]; the possibility of exploring large solution domains, which is crucial in most MOO building problems, while avoiding converging to local optima as aforementioned [111,118–121]; assuring a good trade-off between the required computational burden and the robustness of the optimal solutions achieved [19,106,119,122–124]; a solutions estimation scheme adequate to complex problems as it reduces computational time [106,123–125]; obtaining suitable solutions according to the objective functions when large and sophisticated input data are given [120,121]; GA' structure, presented as the most convenient for the connection with building performance simulation tools and the management of their outputs [27]; its high efficiency in solving complex multi-modal problems when the optimisation is not smooth or when the cost function is noisy [3,111,119,126,127], integer and mixed integer optimisation problems [128] and non-differentiable functions [129]; and being well-suited for parallel computing [4,27,42,53,100].

5. Implementation of GA-based MOO in building retrofit: analysis of evidence

GA-based MOO in building retrofit started attracting greater scientific curiosity around 2013 and displayed a remarkable compound annual growth rate from that year onwards until peaking between 2016 and 2018 with a nearly five-fold increase in scientific publications. In fact, more than half of the primary studies (PS) have been published in the past three years. Fig. 3 displays a graphical summary of the PS between 2000 and 2019, according to publication type. For its majority, they were published in international journals dealing with:

- Energy use, efficiency and sustainability in the built environment (70%):
  E.g. Energy and Buildings (23%), Applied Energy (14%), Energy (5%), Energies (5%), Building and Environment (5%), Energy Procedia, Journal of Cleaner Production, Sustainability, Sustainable Cities and Society, Renewable and sustainable energy reviews, Climate, Indoor and Built Environment;
- Engineering and management journals (14%):

E.g. Journal of HVAC and R Research, Building Services Engineering Research and Technology, Procedia Engineering, Science and Technology for the Built Environment, Journal of Civil Engineering and Management, Journal of Management and Engineering, Automation in Construction, Journal of Building Engineering.

The remaining studies were published in conference proceedings dedicated to the energy, building simulation and engineering field (16%):

- The IBPSA (International Building Performance Simulation Association) conference stands out for its significant gathering of proceedings on simulation and optimisation (11%);
- Other scientific meetings are also found within the PS: e.g. Energy for Sustainability 2015 Sustainable Cities: Designing for People and the Planet, International Conference on Zero Carbon Buildings Today and in the Future, International Conference on Environment/Electrical Engineering and IEEE Industrial and commercial power systems Europe.

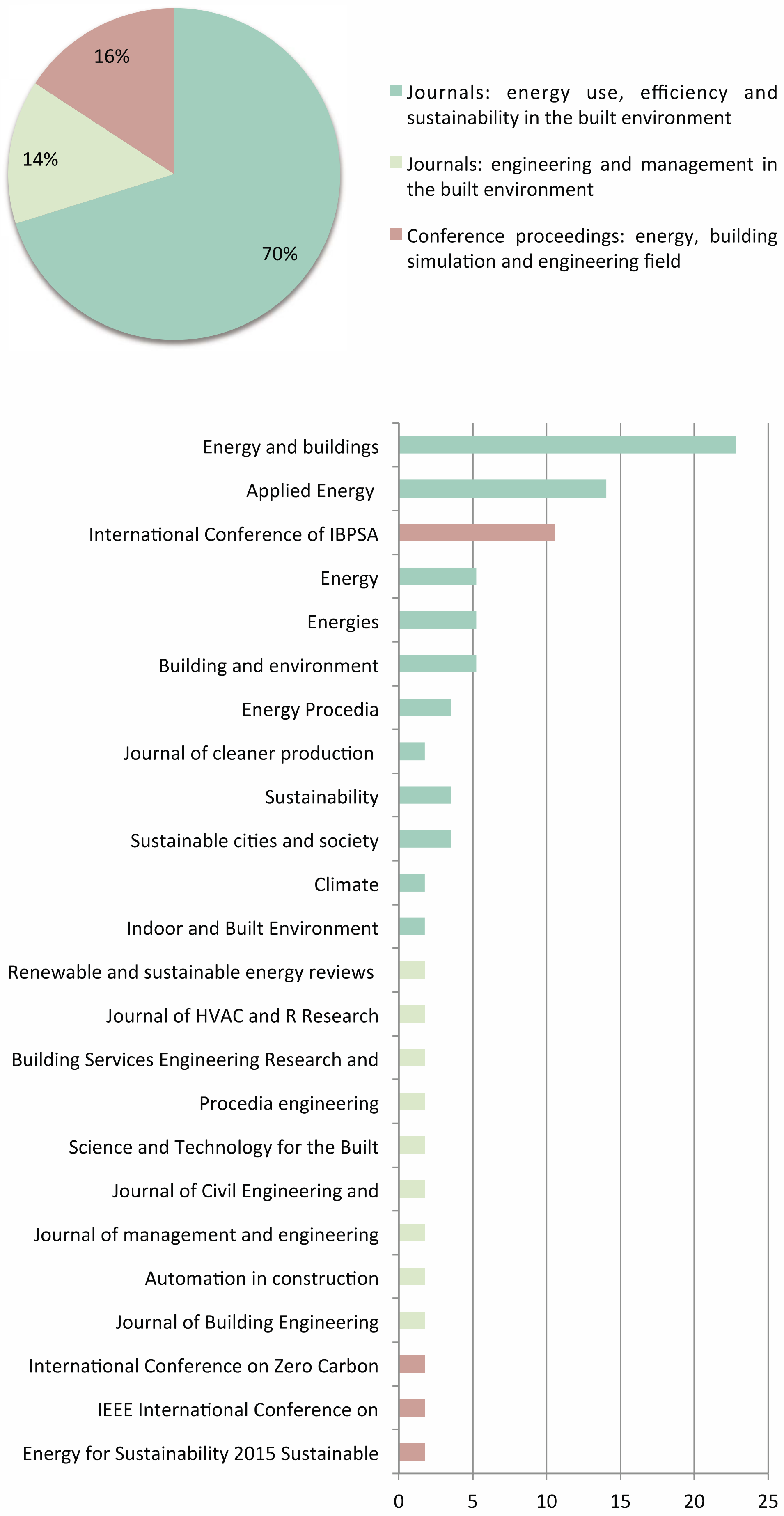

Figure 3. Graphical summary of the primary studies covering building retrofit GA-based MOO from 2000 to 2019.

At the beginning of each analysis subsection, a key findings summary is provided in bullet points, for clarity and impact.

5.1. Case studies characteristics

- Three sustainability scopes are simultaneously addressed in nearly half of the PS: environmental, social and economic;
- Environmental and economic scopes have attracted the most attention while environmental and social paired together are scarcer;
- The majority of PS have chosen real buildings as case-studies, yet archetype buildings are also used. Only 20% worked with simplified building models only;
- Residential buildings are the most covered building use category, followed by educational buildings. Some mixed-use research is also found.

Table 4 displays the main characteristics of the PS: publication details, building use, case study type, location, construction year, and sustainability scopes addressed. The sustainability scopes fall into three categories: environmental (energy and environmental impacts), social (e.g. indoor environmental quality, indoor comfort, impact on occupants' health and productivity) and economic. Nearly half of the PS perform a MOO that covers simultaneously all three sustainability scopes. The coupling of environmental and economic scopes has also attracted an important number of contributions (44%). In contrast, the coverage of environmental and social scopes paired together is scarcer. The most common set of environmental-social trade-offs, between energy consumption and thermal comfort, were explored in [71,127,130–132]. While energy-related objectives represent the majority of the environmental sustainability scope, building emissions were also analysed in several PS and paired with thermal comfort in [109,110,133–135]. On the other hand, the social sustainability scope gives place to a diversity of approaches that go beyond addressing thermal indoor comfort. Roberti et al. [127] explored one of these approaches, by optimising a building's conservation compatibility through a quantitative score system, along with thermal comfort and energy demand. Moreover, Das et al. [136] and Nix et al. [76] studied the trade-off between occupants' health impacts from indoor environment and energy consumption. The gathered data show that the combination of social and economic scopes is yet to be explored. A possible explanation for the social scope receiving less attention than its counterparts might lie in the less immediately tangible feature of these kinds of objectives for building optimisation purposes.

The types of case studies used were classified into the following categories: Real Buildings (RB), Archetype

Building (AB) and Simplified Building Model (SBM). Real buildings account for the majority of case studies (56%). Two publications were found to combine real buildings with other case-study types in their research: Nassif et al. [137] performed a MOO of two case studies, a real building and a simplified building model, both educational buildings. Almeida et al. [138] also analysed two case studies of schools, both archetypes of typical Portuguese schools, however, one is based on an existing school building and the other is an archetype building. Around 20% of PS was found to work with simplified building models only.

Regardless of the case study type, residential buildings are the most covered building use category, followed by educational buildings. Some mixed-use research is also found, combining educational and commercial use [71], as well as commercial and industrial use [139]. Most case studies were built between 1945 and 1980s; the oldest is the medieval building *Waaghaus* [127], followed by Islington's community centre built in the 1890s and retrofitted in 2011 [22], an office building from 1900 [140] and the Civil Engineering Building at the University College Cork built in 1910 [69]. Little work has been shown to address buildings owning any heritage or traditional value and protection, as they are under-represented in this SR, amounting only to 7 studies.

Table 4

Primary studies focusing on GA-based MOO in building retrofit, listed in chronological order.

	Reference	Country	Building use type						Case study type				Case study location	Const. Year	Sustain. scope		
			R	E	C	I	O	H/T/LB	NS	RB	AB	SBM			Env	Soc	Eco
[121]	Wright et al., 2002	UK							■			■	N/A	N/A	■	■	■
[137]	Nassif et al., 2005	Canada		■						■		■	Canada. Montréal	N/A	■		■
[9]	Juan et al., 2009	Taiwan; USA	■									■	Taipei, Taiwan	2001	■	■	■
[141]	Pernodet et al., 2009	France		■							■		France, Agen, Trappes	N/A	■	■	■
[139]	Juan et al., 2010	TW; CN; USA			■	■		■		■			Taiwan	1979	■	■	■
[122]	Magnier et al., 2010	Canada	■							■			Canada, Ottawa	1998	■		■
[142]	Chantrelle et al., 2011	France		■						■			France, Nice	N/A	■	■	■
[131]	Siddharth et al., 2011	India; USA			■							■	India,CN; USA, BC, JUN	N/A	■	■	
[143]	Jin & Overend, 2012	UK		■				■		■			UK, Cambridge	1945/1964	■	■	■
[130]	Gossard et al., 2013	France	■									■	France, Nancy, Nice	N/A	■	■	
[144]	Malatji et al., 2013	South Africa							■			■	N/A	N/A	■		■
[87]	Asadi et al., 2014	Portugal		■						■			Portugal, Coimbra	1983	■	■	■
[136]	Das et al., 2014	UK	■							■			India, Delhi	N/A	■	■	
[145]	Huws & Jankovic, 2014	UK	■									■	UK, Birmingham	N/A	■	■	■
[69]	Murray et al., 2014	Ireland		■				■		■			Ireland, Cork	1910	■		■
[140]	Shao et al., 2014	Germany			■			■		■			Germany, Aachen	1900	■		■
[146]	Wang et al., 2014	UK			■							■	UK, Birmingham	N/A	■	■	■
[123]	Ascione et al., 2015	Italy	■								■		Italy, Naples	N/A	■	■	■
[88]	Carreras et al., 2015	Spain; UK	■									■	Spain, Lleida	N/A	■		■
[147]	He et al., 2015	UK	■								■		England, North-East	N/A	■		■
[134]	Monteiro et al., 2015	Portugal		■						■			Portugal, Lisbon	N/A	■		■
[76]	Nix et al., 2015	India	■							■			India, Delhi	N/A	■	■	
[10]	Penna et al., 2015	Italy	■									■	Italy, Milan, Messina	N/A	■	■	■
[117]	Penna et al., 2015b	Italy	■									■	Italy, Milan, Messina	N/A	■	■	■
[148]	Pernigotto et al., 2015	Italy	■									■	Italy, Trento	N/A	■		■
[149]	Abdallah & El-Rayes, 2016	USA					■			■			N/A	1989	■		■
[138]	Almeida & De Freitas, 2016	Portugal		■						■	■		Portugal, Porto	N/A	■	■	■
[105]	Ascione et al., 2016	Italy					■				■		Italy, Naples	1991-2005	■		■
[133]	Brunelli et al., 2016	Italy		■								■	Italy, Perugia	N/A	■	■	■
[150]	Fresco et al., 2016	Spain	■							■			Spain, Seville	1960	■		■
[71]	García Kerdan et al., 2016	UK		■	■						■		UK, London	1980s	■	■	
[11]	Schwartz et al., 2016	UK	■					■		■			UK, Sheffield	1950s	■		■
[12]	Son & Kim, 2016	South Korea		■						■			South Korea, Seoul	N/A	■	■	■
[151]	Tadeu et al., 2016	PT; Brasil	■							■			Portugal, Amarante	<1960	■		■
[152]	Ascione et al., 2017	Italy			■						■		South Italy	1920-1970	■	■	■
[153]	Ascione et al., 2017b	Italy			■					■			Italy, Benevento	1990s	■	■	■
[106]	Ascione et al., 2017c	Italy	■								■		Italy, Naples	1945-1990s	■		■
[154]	Eskander et al., 2017	Portugal	■								■		PT: LX, EV, OPO, BRG	1970-1980s	■		■
[155]	Fan & Xia, 2017	South Africa	■							■			South Africa	1967	■		■
[156]	García Kerdan et al., 2017	UK		■						■			UK, London	1960s	■	■	■
[22]	García Kerdan et al., 2017b	UK; Mexico					■			■			UK, London	1890s-2011	■	■	■
[132]	Mauro et al., 2017	Italy							■		■		Italy, Milan, Norcia	1970s	■	■	
[127]	Roberti et al., 2017	Italy	■					■		■			Italy, Bolzano	1100s	■	■	
[109]	Ascione et al., 2018	Italy			■						■		Italy, Naples	1970	■	■	■

[157]	Bandera et al., 2018	Spain		■		■		Spain, Pamplona	1975	■		
[158]	Bosco et al., 2018	Italy			■	■		Italy, Rome	1960s	■	■	■
[159]	Cascone et al., 2018	Italy			■		■	Italy, Palermo, Turin	1946-1970	■		■
[107]	Fan et al., 2018	South Africa			■	■		South Africa, Pretoria	N/A	■		■
[128]	Fan et al., 2018b	Sth Afri; China			■	■		South Africa	N/A	■		■
[135]	Jankovic, 2018	UK	■			■		UK, Birmingham	After 1945	■	■	
[160]	Miglani et al., 2018	Switzerland	■			■		Switzerland, Zurich	N/A	■		■
[20]	Sharif et al., 2019	Canada		■		■		Canada, Montreal	N/A	■		■
[110]	Son & Kim, 2018	South Korea		■		■		South Korea, Seoul	1960s	■	■	■
[111]	Ascione et al., 2019	Italy	■				■	GR, Athens; IT, Naples	N/A	■		■
[161]	Ascione et al., 2019b	Italy	■				■	GR, Athens; IT, Naples	N/A	■		■
[162]	Jeong et al., 2019	Rep. of Korea	■			■		South Korea, Seoul	2000			■
[163]	Song et al., 2019	USA; Korea		■		■		South Korea	1974	■		■

R: Residential; E: Educational; C: Commercial; I: Industrial; O: Other; H/T/LB: Heritage/Traditional/Listed Building; NS: Not Specified; RB: Real Building; AB: Archetype Building; SBM: Simplified Building Model; N/A: Not Available/Applicable; Const.Year: Construction Year; Sustain. Scope: Sustainability scope; Env: environmental; Soc: Social; Eco: Economical.

5.2. Optimisation methods, techniques and parameters

The data extraction of optimisation methods and techniques from the PS can be found in a tabulated form at the end of the section (Table 6).

5.2.1. Main optimisation methods and parameters

- Around 80% of the PS use a Pareto-based optimisation concept, either by itself or in combination with an aggregating method;
- Weighting sum approach is the most frequently used aggregating method, followed by analytic hierarchy process and ε-constraint method.

More than 80% of the PS in review use a Pareto-based optimisation concept, either by itself or in combination with an aggregating method (AM). Three types of the commonly popular AM (see description in section 3. Multi-objective optimisation) are applied: the most frequently used is the weighted sum approach [107,121,128,130,141,144,155], followed by the analytic hierarchy process (AHP) [9,127,140] and the ε-constraint method [141]. AHP is implemented in the PS to assign weights to a set of predetermined criteria, identify key elements and support trade-off analysis. Apart from reformulating MOO problems as mono-objective ones, the weighted sum method (WSM) is also adopted in combination with Pareto-based optimisations to contrast its findings [130,141,144]. Additionally, Asadi et al. [87] concluded on the importance of simultaneous MOO and hence on the restrictive character of mono-objective optimisations for the DM process, as it does not allow for the possibility of choosing among optimal solutions nor does it guarantee that a complete Pareto front is found. Others, such as Fan & Xia [128,155], pointed out that the WSM plays an important role in the optimisation process as an interface for decision makers and as a way to achieve the desired performance through weighting factor tuning.

5.2.1.1. Genetic Algorithms

- Fast Non-dominated Sorting genetic algorithm (NSGA-II) is the most popular GA in building retrofit MOO and the most commonly implemented MOGA for multi-objective problems in the field of building research;
- It is employed in the PS primarily on its own, and additionally as a variant or in conjunction with other techniques;
- Overall, PS reported consistent optimal retrofit solutions in a reasonable computational time when other methods would have been infeasible;
- Still, around 20% of PS introduced some type of GA variant, citing the following reasons: overcoming the initial population selection from the generation process, ensuring a higher population diversity and reliable Pareto front evaluation and improving convergence performance in many-objective optimisation problems.

Table 6 shows that Fast Non-dominated Sorting genetic algorithm (NSGA-II) is the go-to GA for optimising multi-objective problems in building retrofit, either:

- As stand-alone form [10,11,12,23,25,76,89,108,110,112,113,115,117-119,121,124-126,128,129,131-134,141,143-146,151,152];
- As a variant [12,88,111,114-116,120,122,130,135,137-139,150];
- In conjunction with other techniques [9,10,76,88,108,110,119-121,124,131,133,138,143].

Developed by Deb et al [164], it is the most commonly implemented MOGA for multi-objective problems in the field of building research [81,164], as well as one of the top efficient MOEA due to its robustness in the convergence toward the true Pareto-optimal front [81,119,164]. Additionally, its efficiency and reliability have been shown in MOO and building performance simulation problems [5,140,156,165,166]. For further details, the interested reader can refer to [15,98,119]. Overall, GAs employed in the PS found consistent optimal retrofit solutions in a reasonable computational time when other methods would have been infeasible [106,132,153]. In [106] in particular, the optimisation of 1.048.576 envelope retrofit scenarios would have taken approximately 10 years, had an exhaustive search method been applied, versus 2 days with GA. More impressive still was the time saving found in [132,153] as a consequence of GA implementation, when contrasted with the exhaustive approach prohibitive hundred of years required to complete the task. Still, as mentioned above, some variants to the algorithm were introduced in around 20% of the PS, alluding to the need of ensuring a higher population diversity and therefore a more reliable Pareto front evaluation on the one hand, and on the other the need for an improved convergence performance when it comes to solving many-objective optimisation problems, with four or more objectives. Regarding the latter, in [12,110] a reference-point based non-dominated sorting genetic algorithm (NSGA-III) based on NSGA-II was developed, and through performance comparison with three other EO algorithms (NSGA-II, MOEA/D, MOPSO) in a many-objective optimisation applied to a public building retrofit, it concludes that NSAG-III showed better performance overall in terms of spacing of non-dominated solutions and average distance, and better diversity and convergence than NSGA-II in the context of a many-objective optimisation. The interested reader can refer to [110] for more details on NSGA-III. Moreover, Ascione et al. [111] concluded that the implementation of a variant of NSGA-II in MATLAB substantially reduced computational time when compared to an exhaustive search approach by more than 98%: the latter would have required 150 days per case study, which would have been infeasible, while the former took 2,5 days per case study, with 106.495 retrofit solutions to be explored.

5.2.1.2. GA-mixed techniques

- The major drawback associated with MOO GA implementation is its time-consuming feature;
- Users generally resort to one of three techniques to avoid computationally expensive building models: very simplified models, very small GA population sizes and/or small numbers of generations or surrogate modelling implementation;
- Surrogate modelling implementation is the most prominent GA mixed-methods technique found in the PS and allows studies to reap benefits from combining the velocity of evaluation of Artificial Neural Network with the optimisation power of GA;
- This mixed-method approach shows much promise regarding time-efficiency when compared to NSGA-II directly linked to an energy simulation tool or exhausting search method, with acceptable accuracy;
- Other GA mixed-methods techniques found in the PS include mathematical programming methods.

Another popular GA-based MOO strategy is to follow a mixed-method approach, generally with the intent to surpass GA's time-consuming feature [76,87,122,130,138]. This issue is often pinpointed as the major drawback associated with GA implementation in MOO, since time-costly simulation evaluations for reaching optimal solutions can turn out to be infeasible. Users generally resort to one of three techniques to avoid computationally expensive building models:

- Using very simplified models while acknowledging its limitations (typically only suitable for research purposes due to oversimplification and inaccurate modelling);
- Selecting a very small GA population size and/or small numbers of generations (possibly affecting significantly the optimisation by narrowing the process to non-optimal solution sets) [101,166];
- Implementing surrogate models, which consist in approximation models that mimic the performance of the original ones at a reduced computational cost [3].

Response Surface Approximation Model (RSA) is an approximation method still quite unexploited that allows for a proper accuracy to be maintained and can be combined with GA for individuals evaluation. The most prominent mixed-methods technique found in this SR uses an RSA method, by combining the velocity of evaluation of Artificial Neural Network (ANN) with the optimisation power of GA [76,87,122,130,138]. Rojas [167] defines ANN as an attempt at modelling the information processing capabilities of biological nervous systems. Based on the main principle of learning, it is composed of layers of parallel elemental units, called neurons, which are connected by a large number of weighted links, over which signals or information can pass. ANNs have to be trained in order to perform tasks: they learn the relationship between the input and output variables by studying previously recorded data and adjusting the weight of neurons. The most used network arrangement is the feed-forward model, composed of several layers of neurons: generally, the layer that produces the network output will be designated as the output layer and all the other layers are called hidden layers. A multilayer feed-forward model is used in all the ANN case studies in the PS. In spite of being quite unexplored still, this approach shows much promise by making the computational time associated with each evaluation negligible: the results obtained emphasise its time-efficiency when compared to NSGA-II directly linked to an energy simulation tool [122] or to an exhausting search method [87], while demonstrating an acceptable level of accuracy. To put it into context, in [87] the whole optimisation process with the ANN model generation using the neural network toolbox took three days, whereas 75 days would have been needed if using an exhaustive search method. Furthermore, in [122] the combination of NSGA-II and ANN resulted in a vast time gain and allowed for a feasible optimisation process that would have otherwise taken more than 10 years, had NSGA-II been directly connected to TRNSYS. While the accuracy reported was excellent (around 1% relative error) for energy consumption prediction, the PMV was generally underestimated. In [138], the use of ANN combined with NSGA-II proved to be effective and useful to approximate complex functions and suggests that after being properly trained, annual computer simulations could be replaced. Nix et al. [76] used ANN to construct a meta-model to replicate input-output relationships based on a sensitivity analysis, to successfully reduce optimisation time. Gossard et al. [130] reduced computation time without compromising the complexity of the problem through training and validation of a multilayer feed-forward ANN to accelerate the calculation of the objective functions based on annual simulations. Ascione et al. [152] developed a multi-stage framework for the robust assessment of cost-optimal energy retrofit solutions (CASA) through the combination of GA-based MOO and ANN. The developed ANNs are successfully used to predict building performance instead of EnergyPlus, with very satisfactory reliability based on a coefficient of regression >0.960 and a relative error <10%. Complementarily, simulation server services can be used as an aid in reducing the computational time required to complete the MOO [11].

Another GA-mixed technique is the implementation of a hybrid algorithm MOO. In [139], GA and heuristic A* graph search algorithm are combined with the aim of overcoming what is described as an ineffective initial population selection from the generation process in traditional GA; the search effectiveness of A* enables the GAA* to overcome it, while maintaining GA's optimisation search for global optimal solutions in a short amount of time.

Lastly, mathematical programming methods were also used in combination with GA in the PS, i.e. mixed integer linear programming [160], nonlinear integer programming [107,155], compromise programming [156] and zero-one goal programming [139].

5.2.1.3. GA input parameters

- GA input parameters are mostly problem-dependent resulting in a wide diversity of research data, as happens with the PS in analysis;
- Around 70% of the PS did provide some information on the genetic parameters and stopping criteria adopted in their MOO, yet often insufficiently detailed or lacking key data;
- The more tailored to the problems' specificities and well designed GA input parameters are, the more efficient and correctly implemented will the GA-based MOO be;
- The input parameters with most impact on computational burden and reliability of GA are the population size and the stopping criterion of maximum number of generations;
- The PS set their GA input parameters based on: expertise and best practice; studied values with the best trade-off between computational burden and Pareto-front proven reliability; software recommended default values;
- The stopping criterion most resorted to within the PS is, by far, the maximum number of generations (75%);

Another important feature to be addressed regarding GA implementation consists in its input parameters and stopping criteria definition. Such parameters are mostly problem-dependent and, while broad recommendations can be found (the interested reader can refer to [112,115]), no official guidelines really exist in the literature due to the impracticality to make general recommendations for setting optimal parameter values. As a result, the data can be quite scattered, as is the case with the PS in this SR. Around 70% of the PS did facilitate some information on the genetic parameters and stopping criteria adopted in their optimisation, yet often insufficiently detailed or missing information. Due to the diversity, inconsistency and lack of data provided, the authors were not able to extrapolate robust conclusions regarding this part of the analysis and furthermore decided not to report these results in tabulated format. However, its main features are acknowledged hereunder.

While some default parameters may adequately fit a range of MOO retrofit problems, such as the crossover and mutation ones, the more tailored to the problems' specificities and well designed the GA input parameters are, the more efficient and correctly implemented will the GA-based MOO be. For setting these parameters and stopping criteria, some PS [20,105,111,123,130,132,144,157,161] have chosen values based on expertise and best practice, as well as those leading to the best trade-off between computational burden and proven reliability of the Pareto front through their own work or previous literature, or values according to the software recommended default parameters. The design of these parameters directly affects GA's performance, convergence rate, the accuracy of the optimal solutions achieved and the computational burden. In particular, the parameters with most impact on the computational burden and GA's reliability are the population size and the stopping criterion of maximum number of generations, since the product of these two parameters provides the limit number of solutions to be explored [153].

The main genetic parameters used in the PS for their GA-based MOO implementation are as follows (for definition of concepts, please refer back to section 4. Genetic algorithm in multi-objective optimisation):

- Population size: it is suggested in the PS that a reliable population size ranges from 2-6 times the number of the design variables in the optimisation [105,106,109,111,123,132,151,153,161]. It was also suggested that a population size of 100 provides a high diversity of solutions, and that surpassing this value is not found to be beneficial while taking more time to converge [144]. Around 30% of the PS adopted a population size of 100 in their MOO, but overall, values range between 10 and 2000;
- Selection type: the binary tournament selection is the most commonly selection method employed in the PS;
- Crossover and mutation rate: it is suggested in the PS that adequately tuning these rates or fractions is important to avoid loss of diversity among individuals of the population throughout the run of the GA and

therefore avoid premature convergence (i.e. when GA gets stuck in local minima or local maxima). The values adopted as crossover fraction range between 0.4 and 1, while mutation fraction ones vary between 0.05 and 0.4;

- Elitism: elitism is generally defined though elitism size, count or rate parameters, but is also presented as rate of individuals or chromosomes that are guaranteed to survive to the next generation in the PS, and is most commonly adopted under the value of 2;

A few additional parameters are occasionally mentioned in some PS, such as the Pareto front population fraction [138], the distribution index for crossover and mutation [122,127,137], the type of crossover (e.g. simulated binary crossover) and mutation (e.g. polynomial), the tournament size [117], the encoding scheme [71,106,109,111,123,132,146,152,153,156], the variable domains [159] and the number of binary digits [159].

As per the stopping criteria (for definition of concepts, please refer back to section 4. Genetic algorithm in multi-objective optimisation) used in the PS, the most frequent are as follows:

- Maximum number of generations: by far the most resorted to stopping criterion within the PS (75%). Some propose, based on their own research, that a reliable maximum number of generations falls within the range of 10-100 generations [105,106,109,111,123,132,153,161]. Others adopt values according to previous numerical tests where it was verified that the solutions did not change beyond a specific number [130]. Though no official recommendations exist, Poli [115] suggests that the most productive search is usually performed in those early generations and that if a solution has not been found by then, it is unlikely that it would be found in a reasonable amount of time. It additionally indicates that, for that reason, the number of generations is typically limited between 10 and 50. 34% of the PS do fall into this category, yet, the spectrum of values used is extremely wide overall, ranging from 15 to 5000, which only emphasises the diversity of these parameters;
- Stall time and generations limit: the number of generations or the time limit with no significant change or where change is inferior to a pre-specified threshold (e.g. by less than 1%) are adopted as stopping criteria in around 16% of PS [9,127,131,136,150,163];
- Time limit and fitness limit: optimisation time and fitness limit applied to the best candidate are seldom used in the PS, around 7% and 11% respectively;

Finally, optimality tolerance is adopted as a stopping criterion in 5 PS and reaching the convergence level, considering the crowding distance (i.e. how close an individual is to its neighbours), is applied in 4 PS.

5.2.2. Optimisation auxiliary techniques

5.2.2.1. Sampling techniques

- A set of sampling and statistical techniques is identified as commonly linked with GA and ANN implementation: Latin hypercube sampling being the most frequent one, followed by the Sobol Sequence Sampling and smart sampling or smart exhaustive sampling technique;
- Other MOO associated techniques found in the PS are penalty and barrier function method;
- The most recurrent constraints employed in the PS are linked to thermal comfort, budget and payback boundaries definition.

Complementarily, a set of sampling techniques is found to be linked with GA and ANN implementation. Latin hypercube sampling (LHS) is one of the most frequently statistical methods used to generate a small and representative sample of a population [76,87,122,152], for specified numbers and ranges of variables [71,76,87,105,122,138,156]. It is frequently used for training and checking ANN validity. It is a space-filling scheme that provides better efficiency than random sampling and guarantees an effective data distribution over the variables space. The Sobol sequence sampling (SSS) is also implemented for the selection of GA initial population [10], which is a quasi-random sequence designed to generate a sample that is uniformly distributed over the unit hypercube. When compared to other sampling techniques such as LHS, it was found to be more effective in exploring the input parameter space [168]. Sobol sequences allow reducing the random behaviour of GA in the initial population generation and avoiding oversampling of the same regions that can occur with random sampling [117]. It is also employed in [148] where NSGA-II is modified with customised sampling, crossover, mutation and selection procedures with the purpose of further increasing its performance. SSS is chosen since it produces uniform samples for high population sizes [168] and the random starting point is obtained through the pseudo-random generator [169]. In the PS it is used in particular to apply the population mutation mechanism through random gene alteration: a gene is randomly selected and replaced by a random value from a uniform distribution that meets the gene range [10,148]. Finally, a smart sampling or smart exhaustive sampling technique is utilised in around 10% of the PS [105,106,109,132,153] at the post-optimisation stage, as a way to conduct constrained cost-optimal analyses for DM regarding the Pareto front solutions found through GA implementation.

A few other MOO associated techniques are used in this SR: in order to prevent from falling into an infeasible domain, the user can resort to approaches such as the penalty and barrier function method to perform a constrained optimisation. Constraints are usually formulated as functions of the variables to be optimised and are most frequently employed in this SR to define thermal comfort [122,130,131,145,146,153] as well as budget and payback boundaries in the optimisation process [9,69,105,123,141,143,144,152,155,156]. Secondarily, they target energy consumption and CO_2 emissions [140,141,144,145], along with insulation material properties [88,140,150].

5.2.2.2. Uncertainty and sensitivity analysis

- Uncertainty analysis and sensitivity analysis are tools with little research in relation to GA-based MOO;
- Around 20% of the PS take uncertainty into consideration in their optimisation process or intend to do so in further work, which can concern any variable that cannot be controlled and can influence intervention performance, from fluctuations in environmental and climatic conditions, material variability, model assumptions, measurements to financial fluctuations;
- Sensitivity analysis is successfully used in several PS to assess the impact or influence of key input variables in targeted or overall outputs and hence evaluate the overall robustness of findings, namely of cost-optimal solutions, and reduce optimisation time.

Sensitivity analysis (SA) and uncertainty analysis (UA) tools are very little researched in relation to GA-based MOO [3,5,76]. Possible explanations for this could lay in the fact that robust optimisation is in its early beginnings in the field of building energy performance [3,76], along with the fact that GA-based MOO in building retrofit is quite a young method (see 5. Implementation of GA-based MOO in building retrofit: analysis of evidence) and not enough research has been conducted to support the maturation of the technique and the high level of expertise needed throughout the whole MOO process, including the acknowledgement of the importance of preliminary statistical analysis and its impact on final results. The lack of standard method approach can also contribute to the small amount of research linking SA and UA and GA-based MOO, and will be addressed further ahead in sections 6.1.2. Challenges and limitations and 6.2.1. Gaps in knowledge and future research needs.

Uncertainty is expressed in variables that cannot be controlled and can crucially influence intervention performance; these can arise from fluctuations in environmental and climatic conditions, material variability, model assumptions, measurement, and financial inflations [133]. However, only around 20% of the PS take it into account in their optimisation process [71,76,106,107,128,133,135,144,145,151,156] or intend to do so in further work [87]. SA is particularly helpful to assess the impact or influence of key input variables in targeted or overall outputs, and therefore to evaluate the overall robustness of findings. Results can then serve an optimisation time reduction purpose, through the use of a selected group of key parameters [76]. Monte Carlo method is commonly used for both UA and SA [71,76,105,133,156]. In [106] a multi-objective approach is employed to identify robust cost-optimal retrofit solutions and assess the resilience to different climatic (global warming) and economic scenarios: the SA performed provides 12 robust cost-optimal energy retrofit solutions depending on the global warming scenario and on the value of discount rate. In [107] a SA is performed to analyse the influence of the discount rate, weighting factors and tax incentive on the proposed model and optimal results, concluding that the energy savings are robust against uncertainty on the discount rate while the economic factors are sensitive to its change. In addition, SA is employed to investigate the robustness of cost-optimal solutions in a few other PS [109,144].

Recognising the importance of the uncertainty entailed in energy performance evaluation, Fan et al. [128] used real-world notch-test data to improve its accuracy. In [152] preliminary large-scale UA and SA of the building energy performance are conducted to support ANNs' generation, through the identification of key parameters that affect the building energy performance, with reference to potential retrofit scenarios and current status. In [135], uncertainty regarding different future climate conditions is addressed through an assessment of resilience, defined as resistance to future uncertainties, at building, site and regional level for different climate years: 2018, 2030, 2050 and 2080. Retrofit options are applied to two semi-detached houses with the intention of publishing post-retrofit monitoring results.

5.2.3. Post-optimisation: Pareto-front ranking methods

- The large number of optimal solutions found in the Pareto front present a challenge and require post-optimisation analysis techniques;
- A handful of non-systematic strategies have been adopted in the PS with the purpose of addressing this gap, resorting extensively to aggregating methods, along with thresholds and multi-criteria decision making methods.

After the Pareto front is found, the sets of optimal solutions can be extremely large and contain an infinite number of solutions. The challenging need of choosing between them is mentioned recurrently [46,106,109,123,140,142,155,156,158,159]. Several non-systematic strategies, thresholds and multi-criteria decision making methods (MCDM) are employed in post-optimisation analyses to obtain the best compromise according to the decision-maker's preferences. In addition to the constraints imposed to the objective functions or range of variables, which already reduce the set of Pareto solutions, the aforementioned aggregating methods (WSM, AHP) are extensively used in the PS for DM support. Compromise programming [156] and multiple-attribute value theory [140] are also adopted as particular kinds of MCDM to choose within the set of Pareto solutions. Moreover, cost-optimal analysis [105,106,109,111,123,132,153], thresholds regarding comfort or heating and cooling load [152], life cycle cost (LCC) analysis [152], minimisation of global retrofits costs [106,153] or total cost solution ranking [147], payback period [154], life cycle analysis (LCA) [20] and conservation compatibility [127] are adopted as final criteria for choosing amongst the retrofit solution sets identified.

5.3. Objective functions and decision variables optimised

The extraction of objective functions and decision variables data from PS can be found in a tabulated form at the end of section 5, in Table 6. A comprehensive additional table, Table 5, was developed focusing on objective function details alone.

5.3.1.Objective functions

- Energy and retrofit cost objectives stand out as the most researched ones (around 60%), followed by comfort objectives (45%), environmental impact objectives and the bottom-addressed objectives, health, and building conservation;
- Different types of energy-related objective functions are found: minimising energy consumption, energy demand, energy load, exergy, and maximising savings;
- Retrofit costs-related objectives are mostly expressed as seeking to minimise initial investment, operating, maintenance and replacement costs as well as payback. Life-cycle cost analysis and net present value concepts are also applied;
- Comfort objectives, mostly linked to thermal comfort, mainly aim at reducing thermal discomfort hours by either setting a limit or resorting to thermal comfort formulas and indexes. The Predicted Man Vote index (PMV) is found to be the most prevalent one, followed by the Predicted Percentage of Dissatisfied (PPD);
- Environmental impact objectives are most frequently emissions related, with strong interest emerging regarding LCA as well.

Energy and retrofit cost linked objectives stand out as the most researched ones (around 60% of cases), generally within a two-objective optimisation, or analysing trade-offs with comfort objectives, and less commonly environmental impact. Energy, cost and comfort related objectives are simultaneously targeted in approximately 20% of cases (Table 6). Several types of energy-related objective functions are found in PS:

- Minimising energy consumption [10,12,117,123,130,131,133,136,140–143,20,144,146,148,153,158,159,22,71,76,87,105,106,110];

- Energy demand [69,87,106,109,123,127,132,147,150,151,153,157,159];
- Energy load [138];
- Exergy [22,71,156,157];
- Maximising savings [107,128,134,154,155,163].

The objective functions associated with retrofit costs are generally expressed as seeking to minimise initial investment, operating, maintenance and replacement costs as well as payback, although life-cycle cost (LCC) analysis [9,11,20,56,138,163] and Net Present Value (NPV) [9,10,22,107,117,133,148,155,156,162] concepts are also applied.

Nearly half the PS target comfort objectives, mostly linked to thermal comfort [10,12,123,127,130–133,135,137,138,142,22,145,156,158,56,71,87,109,117,121,122]. These tend to follow one of two formulas: reducing hours of thermal discomfort or maximising hours of thermal comfort, by either setting a limit, e.g. number of hours above 25ºC or previous baseline [131,132,135,138,153], or resorting to thermal comfort formulas and indexes such as the Predicted Man Vote Index (PMV), Predicted Percentage of Dissatisfied (PPD) and the Isum Summer Comfort Index (Isum) [22,56,132,137,142,156,158,71,87,110,121–123,127,130]. PMV is found to be the most prevalent one, followed closely by PPD. Only one study targets Indoor Environment Quality (IEQ) along with PPD, in a three-objective optimisation looking at the trade-offs between comfort, cash payback period and carbon payback period [143].

Environmental impact linked objectives are most frequently emissions related [12,69,162,109,110,133,135,140,145,149,160], but LCA is attracting interest as well [20,88,142,143]. Life cycle carbon footprint (LCCF) [11] and Natural-resource consumption [139,149] are also addressed.

Health and building conservation are at the bottom of the objective functions addressed in the PS (around 8%). The former is analysed in [76,136], specifically looking at the trade-off between health impacts from exposure to indoor heat, cold and PM2.5 and energy consumption. The latter is explored in [127] along with energy demand and thermal comfort, through the quantification of the concept of conservation compatibility of energy retrofits by following an AHP based on conservation scores from expert opinions.

5.3.2. Decision variables

- Four major decision variables categories have been identified in the PS: building envelope, building systems, renewable energy technology, and building control strategies;

- The building envelope category makes up for the overwhelming majority of decision variables in GA-based MOO in building retrofit. Amongst its variables, window options primarily, and secondarily external walls and roof thermal transmittance (U-value), attract the most research attention;
- Mechanical systems variables rank in second place in frequency and include heating, cooling, and lighting variables. The most prevailing ones are linked to HVAC type;
- Renewable energy technologies incorporation into buildings include decision variables in solar and wind energy, the most frequently analysed being the type of solar thermal collector and photovoltaic system;
- The building control strategies category assembles all variables related to mechanical systems control, comprising HVAC system settings and temperature set point control measures, lighting power options and control settings, building automation control system efficiency and shading control measures.

The decision variables selected in the PS mainly fall into four major design categories (see Table 6):

- Building envelope;
- Building systems including heating, cooling, and lighting;
- Incorporation of renewable energy technologies into buildings;
- Building control strategies.

Several studies make use of SA to maintain a reasonable number of decision variables (see section 5.2.6. Uncertainty and sensitivity analysis).

The building envelope section makes up for the overwhelming majority of the decision variables in GA-based MOO in building retrofit. It encompasses firstly window options (number of layers, low emissivity coating option, void gas type, frame type), which is found to attract the most research attention [10–12,20,22,69,71,76,87,105–107,109–111,117,123,127,128,132–134,138–143,145,147,148,150–156,158–161,163]. Additionally, other variables related to window thermal performance are considered for optimisation: total solar energy transmittance (g-value), heat transfer coefficient (U-value) [22,109,138,150,157,159,160,162] and window-to-wall ratio [11,20,76,122,141,143,145,146,154].

The second most frequent variables are linked to the external walls and roof thermal transmittance (U-value), also presented as insulation thickness [10,11,22,69,71,76,105–107,109,111,117,123,127,132,134,135,138,141,145,147,148,150–154,156–163]. Ground floor, ceiling and internal partitions insulation are analysed as well [10,11,71,117,127,148,151,156,160]. Other thermal performance features of walls and roofs are covered, such as: thermal conductivity and density [76,88,130,136], solar radiation absorption coefficient, also expressed as thermal emissivity

[20,76,153,161,105,106,109,111,123,132,136,152]. Furthermore, the type of insulation material related to walls, roofs, and in a lower degree, ground and basement floors [12,20,143,145,150,155,156,158,22,71,87,107,110,128,140,142] is found to be accountable for one of the most common decision variables studied in the PS. Other variables optimised within the building envelope category include wall configuration encompassing PCM properties [159], air tightness rate variation [9,20,156,160,22,69,76,127,135,136,140,141], sealing options [71,156] and solar shading related variables namely façade installation, shading type and shade factor (interior or exterior shading systems, blinds, overhangs) [20,76,105,109,136,150,152,159,161,162].

Decision variables concerning the type of mechanical systems rank second place in frequency after building envelope ones, in particular regarding HVAC type [9,10,12,20,69,71,87,105–107,109,110,117,123,128,132,133,136,139,140,144,148,151,153,154,156,160,161,163]. Some distinguish between boiler type options (gas condensing, natural gas, standard, modulating, oil, heat pump, biomass, etc) [10,22,69,105,109,117,132,133,135,148,151,152,154,156,160], chiller type (installation, air-cooled, water-cooled, standard, high-efficiency electric etc) [22,105,109,127,131–133,152], HVAC energy efficiency [20,22,107,132,133,139,153,154], mechanical ventilation system options and heat recovery [9,10,20,117,123,136,148,163]. Other ventilation strategies are optimised including air change rate variation and fans [9,76,127,136–138,145], circulating and outside air [131]. Finally, lighting system efficiency [20,22,71,107,133,144,154,156,162,163], HVAC components size [121], appliances energy efficiency [111,154] and DHW energy efficiency [132] variables are also explored.

The incorporation of renewable energy technologies in buildings is grouped under a separate section from building systems, due to its specificities and research interest in MOO. It includes decision variables in solar and wind energy: type of solar thermal collector [87,105,128,133,145,151,155,160], photovoltaic system [20,22,105,107,109,111,132,135,145,151–153,156,160,161,163], thermosyphon and solar thermal forced circulation [151] and wind power [22,145,156].

Finally, the building control strategies category assembles all variables related to mechanical systems control, including HVAC system settings and temperature set point control measures [20,22,145,146,152,153,156,158,170,109,121–123,131,132,135,137], lighting power options and control settings (motion sensor, etc) [20,141,144,163], building automation control system efficiency [133] and shading control measures (automatically-controlled shading equipment) [142,161].

Only two decision variables found in the PS fall outside of the previous design categories: clothing level, analysed in [135], and hourly schedules for these technologies in [160].

Table 5

Objective functions addressed in primary studies, listed in chronological order.

Ref.	Energy						Retrofit cost								Comfort			Environmental impact					Health	Conservation
		Cons	Dem	Sav	Load	Exergy		IIC	OC	MC	RC	NPV	LCC	Payback		Thermal	IEQ		Emissions	NRC	LCA	LCCF		
[121]							■		■						■	■								
[137]	■	■													■	■								
[9]							■					■	■					■						
[141]	■	■					■	■	■	■														
[139]							■	■		■								■		■				
[122]	■	■													■	■								
[142]	■	■					■	■							■	■		■			■			
[131]	■	■													■	■								
[143]							■							■	■		■	■			■			
[130]	■	■													■	■								
[144]	■			■			■							■										
[87]	■	■	■				■	■							■	■								
[136]	■	■																					■	
[145]							■	■							■	■		■	■					
[69]							■	■	■					■				■	■					
[140]	■	■					■	■										■	■					
[146]	■	■					■	■																
[123]	■	■	■												■	■								
[88]							■	■	■									■			■			
[147]	■		■				■	■																
[134]	■		■				■	■																
[76]	■	■																					■	
[10]	■	■					■	■	■		■	■			■	■								
[117]	■	■					■	■	■		■	■			■	■								
[148]	■	■					■					■												
[149]							■	■										■	■	■				
[138]	■				■		■						■		■	■								
[105]	■	■					■	■	■															
[133]	■	■					■					■			■	■		■	■					
[150]	■		■				■	■																
[71]	■	■				■									■	■								

[11]						■						■	■			■			■	
[12]	■	■				■	■		■			■	■							
[151]	■		■			■	■		■											
[152]	■	■				■	■	■		■				■	■					
[153]	■	■	■											■	■					
[106]	■	■	■																	
[154]	■			■		■	■													
[155]	■			■		■					■		■							
[156]	■				■	■					■			■	■					
[22]	■	■			■	■					■			■	■					
[132]	■		■											■	■					
[127]	■		■											■						■
[109]	■		■			■	■	■						■	■	■	■			
[157]	■		■		■															
[158]	■	■				■	■							■	■					
[159]	■	■	■			■	■													
[107]	■			■		■							■							
[128]	■			■		■							■							
[135]														■	■	■	■			
[160]						■	■	■								■	■			
[20]	■	■				■						■				■		■		
[110]	■	■				■	■							■	■	■	■			
[145]						■	■							■	■	■	■			
[111]	■	■				■	■	■												
[161]	■	■				■	■	■												
[162]						■	■				■					■	■			
[163]	■			■		■						■								

Cons: Consumption; Dem: Demand; Sav: Savings; IIC: Initial Investment Costs (retrofit actions + labour); OC: Operating costs; MC: Maintenance costs; RC: Replacement costs; NPV: Net Present Value; LCC: Life cycle cost; IEQ: Indoor environment quality; NRC: Natural-resource consumption; LCA: Life cycle analysis; LCCF: Life cycle carbon footprint.

5.4. Simulation-optimisation approach and tools

Building energy optimisation tools (BEOTs) have been collected, classified and compared in previous research [1,4,6]. The literature globally agrees on a four-group classification for BEOTs:

- Generic or stand-alone optimisation tools: commercially available embedded with optimisation algorithms, requiring external input from energy simulation software to perform energy optimisation. They allow users great freedom in the definition process and can additionally be used for tasks of other nature (e.g. ModelCenter, modeFRONTIER, GenOpt, MATLAB, Dakota, and Topgui);
- Simulation-based optimisation tools: based in mature energy simulation software, where the optimisation engine is encapsulated and tightly linked to the simulation engine (e.g. BeOpt, Opt-E-Plus, DesignBuilder optimisation module);
- Optimisation engine oriented tools: primarily designed for building energy efficient design optimisation. They own a native optimisation engine and use an imported energy simulation program (e.g. jEPlus+EA, Grasshopper, MOBO, ENEROPT, GENE_ARCH, MultiOpt 2);
- Customised tools: the user can code his own tool integrating simulation and optimisation in several programming languages (e.g. Fortran, C++, C, Visual Basic in Microsoft Excel).

Furthermore, the integration between BEOTs and building performance simulation (BPS) tools has been reviewed in detail in several previous studies. For more insight into this topic, the reader is referred to [1,3,4,6,69]. Additionally, a number of comprehensive reviews on building energy simulation packages, such as EnergyPlus, eQuest, DOE-2, ESP-r, BLAST, HVAC-SIM+, TRNSYS, IDA-ICE, have also been published in the last decade. The interested reader can refer to [171,172].

5.4.1. Simulation-optimisation approach

- Two main simulation-optimisation approaches are adopted in the PS: dynamic simulation, based on detailed or simplified models, or static modelling approach;
- EnergyPlus is the most used dynamic simulation software employing an energy simulation engine, followed by TRNSYS. Other energy simulation tools used in the PS are: DesignBuilder, DOE 2.2, Comis, eQuest, Design Advisor, IDA ICE;
- Occasionally, modelling tools such as Sketchup and REVIT are paired with the chosen energy simulation tool;
- Fewer PS couple static simulation modelling with optimisation techniques.

The optimisation-based PS reviewed were found to adopt mainly one of two approaches: a dynamic simulation, based either on detailed or simplified models, or a static modelling approach, i.e. a system representation at a particular point in time.

In the first one, the extensive use of EnergyPlus is evident, accounting for slightly more than half of the PS employing an energy simulation engine [11,12,111,123,127,132,135,136,138,143,145,146,22,147,152–154,156,157,159–162,71,76,88,105,106,109,110]. In short, EnergyPlus is an open source energy analysis and thermal load simulation tool, comprising modular structured code written in Fortran. It inherits its major simulation characteristics from the BLAST and DOE-2 programs [173]. TRNSYS comes second after EnergyPlus [10,87,117,122,130,142,148]. It is a tool with a modular system structure, designed for the transient system simulation of complex energy systems problems, with demonstrated flexibility allowing for different configurations [174]. A possible explanation for its popularity lies in the fact that some optimisation tools are specifically designed to be coupled with EnergyPlus and TRNSYS (e.g. JEPlus+EA) and that EnergyPlus has several user-friendly add-ons (e.g. DesignBuilder). Adding to this, they are easily coupled with external software due to its text-based inputs-outputs. DesignBuilder [175], the graphical interface for EnergyPlus, is used for simulation in [20,106,109,138,145,162] and subsequently for optimisation, through the articulation with separate optimisation tools or using its native optimisation module (see 5.4.2. Simulation-optimisation tools). Other energy simulation tools used within the PS are: DOE 2.2, Comis, eQuest, Design Advisor, IDA ICE [131,139,142,149,158]. Complementarily, some authors use modelling tools coupled with a chosen energy simulation tool, such as Sketchup and REVIT. Schwartz et al. [11] used it as the first of four tools adopted in their optimisation process: Sketchup, EnergyPlus, JEPlus, and JEPlus+EA. Eskander et al. [154] used REVIT to model the geometry of four detached residential case studies and combines it with EnergyPlus to perform its initial simulation and calculate the annual heating and cooling needs based on the comfort requirements of the Portuguese legislation; the aim of the MOO was to select the best set of retrofitting measures applied to four different regions, that would maximise the annual energy savings while minimising the initial investment. Sharif & Hammad [20] modelled its case study in REVIT before importing it to DesignBuilder to provide input data and integrate BIM tools with energy simulation.

MATLAB is also used in the simulation process, through sampling generation following the LHS method [76]. In two PS [22,71,156], Python programming language was used for exergy performance simulation and analysis.

There are fewer examples of static simulation models being coupled with optimisation techniques [69,134,137,141]. Murray et al. [69] made a case for static simulation based on the lack of accessibility to high-end computationally intensive dynamic energy models. It adopted the simplified degree-days method according to the CIBSE Guide TM41 [176] combined with GA. Nassif et al. [137] employed a steady-state model for a mathematical HVAC optimisation to determine the setpoint values of the supervisory control strategy of the HVAC system for the operating consumption energy and building thermal comfort, with constraints on the HVAC system operation. Pernodet et al. [141] made use of a polynomial function in order to estimate the energy consumption for the energy objective function, bypassing the use of dynamic thermal simulation. It further suggested that it would be interesting to couple a dynamic thermal simulation tool with the Real-Coded GA genetic solver and that the model could be adapted to other types of buildings and climates. Monteiro et al. [134] developed a simplified thermal model for the optimisation of energy needs and cost reduction, based on indicators and parameters defined by the Portuguese standard of Energy Performance of Buildings DL118/2013 [177] and coupled NSGA-II with this static method approach. Fan et al. [107] mathematically modelled the energy consumption of the various components of a building for a MOO maximising energy savings and reducing the payback period of the retrofit of an office building in South Africa, with the objective of complying with green building policy.

5.4.2. Simulation-optimisation tools

- Generic tools are the most adopted ones within the PS, in combination with EnergyPlus and TRNSYS. MATLAB in particular, although not designed specifically for building optimisation, is the optimisation tool of choice for GA-based MOO retrofit studies;
- Simulation-based optimisation tools are also applied, namely DesignBuilder's optimisation module and jEPlus;
- jEPlus+EA, an optimisation engine oriented tool, comes in second place after MATLAB within the most used optimisation tools;
- Customised design optimisation techniques are used as well, in particular for introducing energy standards coding into the optimisation process.

Generic optimisation tools are the most used within the PS, in combination with energy simulation software EnergyPlus and TRNSYS. Even though MATLAB is not specifically designed for building optimisation and requires a higher expertise level [3], it is the optimisation tool of choice for GA-based MOO retrofit studies [10,76,136,138,143,148,152–154,161,87,105,106,109,111,117,123,132]. In a nutshell, MATLAB is an interactive environment for numerical computation, visualisation, and programming that can be used for a wide range of applications [178]. MATLAB Optimisation Toolbox™ provides a variety of algorithms for optimisation problems that can solve constrained and unconstrained continuous and discrete problems. Moreover, its Neural Network toolbox allows reducing computational time through surrogate models, which is an additional feature that can further contribute to its success amongst the building optimisation community. In [159], Python was chosen for coupling the implementation of the NSGA-II algorithm with a building energy model built in EnergyPlus. GenOpt [179], another generic optimisation tool, was developed to yield the minimisation of linear cost functions. It can be coupled with any external simulation program, provided that its inputs and outputs are expressed in a text-based format (e.g. EnergyPlus, TRNSYS, DOE-2, IDA-ICE, SPARK, BLAST). However, because of its inability to handle MOO problems, GenOpt is only considered in this review for its capacity to conduct parametric studies and statistical databases [87,122]. In [130] GenOpt is coupled with TRNSYS to generate random data sampling sets for ANN learning and validation and is additionally used for constraint definition on summer comfort index through the penalty function method.

A simulation-based optimisation tool is used in two of the PS. As previously stated, DesignBuilder is used in several PS as a graphical interface for EnergyPlus simulation, and in addition its optimisation module is employed to target different objective functions: Huws & Jankovic [145] used DesignBuilder's optimisation module and jEPlus to conduct a MOO to reduce carbon emissions, construction cost and attain thermal comfort, while in [20], the case study was modelled in REVIT and imported to DesignBuilder to perform a MOO concerning three objectives: total energy consumption, LCC and LCA, optimised by pairs due to software limitations.

jEPlus+EA, an optimisation engine oriented tool, takes second place within the most used optimisation tools after MATLAB [11,22,71,88,135,145,147,156,157]. It couples jEPlus, the Java shell to perform parametric analysis for EnergyPlus, with a modified NSGA [180]. Another optimisation engine oriented tool based on NSGA-II, MultiOpt, is designed specifically for retrofit solutions optimisation [142]. The tool, with three components (graphical user interface (GUI), GA and a set of assessment methods) was applied to a school case study, in combination with dynamic simulation software TRNSYS and COMIS, regarding its building envelope, HVAC systems and control strategies. In [158] MOBO, another optimisation engine oriented tool, was coupled with IDA ICE to perform a MOO using MOBO's NSGA-II, to minimise the annual total energy consumption, discomfort hours and investment cost of an office building in Rome.

Finally, some customised design optimisation techniques are found amongst the PS, in particular for incorporating energy standards coding into the optimisation process, such as Visual Basic for Applications (VBA) in Microsoft Excel. In [138], VBA was used for training and validating the ANN for the optimum building envelope insulation thickness, in combination with DesignBuilder, EnergyPlus and MATLAB toolbox. In [140] it was used for implementing the building energy simulation module based on the standard DIN V 18599, a holistic performance assessment method developed for German non-residential buildings. Jeong et al. [162] built a VBA model for a GA-based MOO with 5 cost and environmental objective functions to promote the improvement of multi-family housing complexes energy efficiency in South Korea; the benefits of employing a VBA model due to its user-friendly and simple graphical interface, allowing for a wider access to non-expert users, are advocated in the study. Other customised optimisations were found to use C programming coupled with EnergyPlus [127]. Contreras et al. [150] enhanced the utility of combining simplified building models with optimisation tools versus the high computational cost of detailed energy models: the authors code the standard energy calculation approach in ISO 13790 and EN 15217 in MS excel programming and used the GA included in the MS Excel Solver tool for the optimisation. Other optimisation studies coded simplified dynamic models of buildings: Wright et al. [121] used the lumped capacitance model to approximate the transient conduction in a ventilation slab system and building fabric.

The simulation-optimisation exhaustive list can be found in Table 6 at the end of section 5.

5.5. Historical, traditional or special architecture value buildings

- The historical, traditional or special architecture value buildings category has been overlooked in GA-based MOO in building retrofit;
- The most prevalent objectives for trade-off analysis are linked to retrofit costs, entailing payback, life cycle cost and cost of energy consumption, along with the environmental impact of buildings. Indoor comfort is found to attract less attention followed by conservation compatibility;
- The process of defining and quantifying intrinsically qualitative objective functions, as in aesthetics, urban integration, and conservation compatibility, is particularly challenging. Analytic hierarchy process (AHP) was used in the PS as a method to overcome these quantification issues.

The challenges entailed in MOO in sustainable and energy-efficient building retrofitting are all the more evident when buildings own any kind of heritage, traditional or special architecture value and protection. It is well known that the retrofit of these types of buildings is subjected to more constraints, strict regulations and uncertainties, in particular in vernacular and traditional context, and requires more care than general building retrofit [181,182]. When translated into the MOO process, these specificities make an inherently difficult problem become all the more challenging, as a robust optimisation in these cases should incorporate aesthetics, conservation compatibility or analogous values in some way, which are all intangible by nature. However, in practice too often a higher efficiency level is obtained with disregard to the building's heritage value. For this reason, a separate analysis is performed for this category.

Juan et al. [139] and Jin et al. [143] focused on all three sustainability scopes, while Murray et al. [69], Schwartz et al. [11], Shao et al. [140] and Ascione et al. [111,161] examined environmental and economic optimisation topics, and Roberti et al. [127] looked at environmental and social issues. All studies tackled three-objective optimisation problems, except for [11,111], and relied on real-building case studies with residential [11,127], educational [69,143], commercial [139,140] and industrial [139] uses, except for [111,161] which relied on a residential building archetype. The most common objectives for trade-off analysis are linked to retrofit costs, including payback, life cycle cost and cost of energy consumption, along with the environmental impact of buildings. Indoor comfort [127,143] is found to attract less attention followed by conservation compatibility at the less-explored end of the spectrum [127]. GA is employed in the form of either stand-alone, hybrid or within GA-mixed techniques. NSGA-II is the most established GA in this category as well. Both dynamic and static modelling approaches are used, with EnergyPlus once more ranking as the most prevailing software for modelling and dynamic simulation. A diversity of tools (i.e. generic optimisation tools, optimisation engine oriented tools, customised design optimisation techniques, and mathematical programming methods) are used for solving MOO.

A noteworthy feature of Roberti et al.'s [127] research lies precisely in the inclusion of conservation compatibility as an objective function for a medieval historical house MOO in Italy, assigned to become a museum. It distinguishes itself from other heritage-based MOO studies, as energy savings or higher comfort levels objectives are too often obtained at the expense of heritage degradation. A mixed-mode optimisation approach is followed, combining EnergyPlus simulation, NSGA-II in C original implementation and AHP to find the trade-offs between heating and cooling energy demand, thermal indoor comfort and conservation compatibility. Different decision variables concerning the building envelope (insulation, air tightness, glazing) and systems (ventilation and cooling) were considered. A three-stage process was followed by firstly defining the technically feasible energy efficiency measures, secondly quantifying the concept of retrofit conservation compatibility and finally conducting the MOO. Conservation compatibility was quantified through AHP, obtaining scaled conservation weights and an expert score-based scheme. The sum of conservation scores matching each retrofit measure built up the overall retrofit conservation compatibility.

In like manner, Shao et al. [140] combined AHP and NSGA-II, yet with an emphasis on the integration of the numerical optimisation process and the analysis performed by design teams. Three main objectives were targeted for minimisation regarding the energy retrofitting of existing office buildings: operational energy consumption, environmental impact GWP and retrofit cost, with constraints concerning envelope insulation, energy consumption, envelope air leakage, indoor air quality, and thermal comfort. The decision variables encompassed variations at the building envelope level, HVAC system, and renewable energy incorporation. After obtaining the Pareto-front optimal solutions, features were compared and ranked by applying MCDM techniques to further aid the design team with the DM process.

As previously mentioned, [69] used a static simulation approach, by combining GA with the simplified degree-days modelling technique to optimise the Civil Engineering Building from the University College Cork built in 1910. It explored trade-offs between payback period, CO_2 emissions and energy consumption cost, for a capital investment cost constraint. The decision variables are building envelope (insulation thickness, window type, envelope air tightness), HVAC systems (boiler type) and renewable energy related.

Jin et al. [143] and Schwartz et al. [11] conducted a Pareto-based MOO for an educational and residential building respectively, both located in England. In [143] the research focused on the steel-framed Inglis Building from the Department of Engineering, University of Cambridge built in 1945, with reinforced concrete floors. Both studies coupled EnergyPlus modelling with MATLAB for the implementation of a constrained optimisation with NSGA-II, looking at the trade-off between cost, energy use and user productivity to identify optimal façade solutions while taking into account carbon and cash payback constraints. Schwartz et al. [11] used NSGA-II to optimise the retrofit of a council housing complex, grade II listed building, varying the building envelope properties in terms of thermal insulation, window type, and window-to-wall ratio. It examined the trade-off between the building's environmental impact, using the life cycle carbon footprint (LCCF), and its life cycle cost (LCC) for a life span of 60 years. Apart from EnergyPlus for modelling thermal properties, the authors used Sketchup for geometric modelling, jEPlus for the generation of new models based on the combination of different design parameters and jEPlus+EA to define the objective functions and the genetic process. Even though the method successfully found optimal solutions within a reasonable amount of time, it is suggested that a mono tool could be developed with a simple user-friendly interface to avoid preventable mistakes stemming from the integration of four different tools.

Juan et al.'s [139] method stands out due to the use of a hybrid GA with the A*graph search algorithm, GAA*. This technique feeds from the feedback between both algorithms, with the intention to overcome traditional GAs' random initial population selection, while keeping the diversity of global optimal solutions due to its mutation mechanism. The goal was to develop a DM support system, for the evaluation of existing office buildings and the recommendation of an optimal cost-effective set of retrofit actions. The objectives were the cost of all retrofit actions, building quality and environmental impact, while the retrofit measures included intervention at building envelope, HVAC system, and building control systems level. An algorithm effectiveness validation was performed, comparing the robustness of GAA* with a stand-alone GA and Zero-One Goal

Programming (ZOGP), finding GAA* to be more robust in terms of efficiency and solution quality. It also examined the technique's potential for practical application through comparison with a real project.

Finally, Ascione et al. [111,161] conducted a MOO based on a NSGA-II variant aiming at reducing primary energy consumption and global cost with reference to two case studies: a modern villa located in Athens and a traditional tuff-made villa located in Naples. By coupling EnergyPlus with MATLAB, 9 retrofit measures were studied, including the improvement of HVAC systems 'efficiency, PV system installation, window replacement and roof and external walls thermal insulation. As with many other PS, a post-optimisation MCDM was then conducted according to two different criteria: the achievement of the nearly zero energy standard and cost-optimality. Lastly, it is suggested that its findings can contribute to providing useful generic guidelines for Mediterranean coastline housing retrofit regarding energy-efficiency and cost-effectiveness.

Table 6

Extraction of primary studies main data for analysis, listed in chronological order.

Ref.	MOO Methods	Opt. topic				Objective functions	Decision variables	Constraints	Sampl.	U.V.		S|M tools	Aux. Opt. Tool
		Env	Sys	BCS	RES					Y	N		
[121]	GA (MOGA) Pareto front Aggregating method of constraints		■	■		the assessment period (30 years) Thermal discomfort (%): PPD Infeasibility objective (aggreg. constraints viol.)	HVAC control system set points HVAC components size	Coils design Supply fan HVAC capacity	N/A		■	Lumped capacitance model	N/A
[137]	GA (NSGA-II) Pareto front Penalty Function method: constrained opt.		■	■		Operating energy consumption (kWh) (reheat + chiller + fan) Thermal comfort (%): PPD, PMV	HVAC set points (zone t^{o}C; supply duct static pressure; supply air t^{o}C; chilled water supply t^{o}C required reheat; min outdoor ventilation airflow rate)	Fan airflow rate Zone airflow rate PPD of each zone	N/A		■	Steady-state model	N/A
[9]	GA + Analytic hierarchy process (AHP) Pareto front Constrained optimisation	■	■	■		Retrofit cost ($): NPV and LCC (initial investment cost; annual energy saving; income of an action; annual retrofit action cost; expected lifespan of an action; residual value; discount rate) Retrofit quality (weighted score scheme)	Building envelope repair and roof waterproofing Kitchen exhaust fan installat. + plumbing replacement Envelope air tightness (m^3/h.m^2 @ Pa) Walls and windows soundproofing Efficient water management system Recyclable materials Security features and devices	Budget (IC) Quality priority constrained by user's decision and threshold	N/A		■	Java Server Pages Java environment Apache Tomcat web container MySQL database	
[141]	GA (GenetikSolver V4.1) Pareto front Aggregating method (Weighted sum approach + ε-constraint method) Penalty Function method: constrained opt.	■	■	■		Energy consumption (kWh/m^{2}year) Retrofit cost (€): initial investment cost Global cost (€): initial investment cost + annual energy cost + annual maintenance cost + inflation and discount rate	Roof and walls U-Value (W/m^{2}K) Window-to-wall ratio (%) Window type: U-value (W/m^{2}K) and G-value (%) Envelope air tightness (m^3/h.m^2 @ Pa) Lighting power options and control settings	Retrofit cost Energy consumption	N/A		■	Polynomial function	Real-Coded GA GenetikSolver V4.1
[139]	GAA*: GA + A* graph search algorithm Stand-alone GA Zero-one goal programming (ZOGP)	■	■	■		Retrofit cost ($): sum of retrofit actions costs Building quality Environmental impact	Roof type: roof garden/vegetated roof Exterior pavement and adaptable design strategies HVAC system type: energy efficiency Window type: insulation, low-e coating + shading Building structure insulation IEQ; daylight and artificial lighting Energy, water and waste management system Recyclable materials	N/A	N/A		■	Design Advisor	N/A
[122]	GA (NSGA-II) + ANN (multilayer feed-forward) Pareto front Penalty Function method: constrained opt.	■	■	■		Energy consumption (kWh/m^{2}year): Furnace EC + Cooling EC + Fan EC Thermal comfort (hours): PMV	HVAC system settings and thermostat programming Window-to-wall ratio (%) Thermal mass thickness (m)	Thermal discomfort hours	LHS		■	TRNSYS GenOpt	N/A
[142]	GA-based (NSGA-II) Pareto front Economic and environmental databases	■	■	■		Energy consumption (kWh/m^{2}year) Retrofit cost (k€): initial investment cost Thermal comfort (hours): PPD index	Roof, external wall and ground floor materials type Internal partition wall and intermediate floor type Window type: layer N^o, low-e coating, void gas	N/A	N/A		■	TRNSYS COMIS	MultiOpt

						EI: LCA of building materials (CO_2e units)	Control strategies: cooling and shading						
[131]	GA + statistical approach Multiple nonlinear regression applied to the generated data sets Constrained optimisation		■	■		Energy consumption (kWh): Total electricity (kWh) + Total natural gas consumption (therms converted to kWh) Thermal comfort (level)	Area per person (m^2/person) Circulating (m^3/s) and outside air (m^3/s person) Min/max supply temperature (^{o}F) Bypass factor of the DX coils Electric input ratio of chiller (=1/COP) Supply fan efficiency and economizer limit (^{o}F)	Comfort T^{o}C limits	N/A		■	DOE 2.2	N/A
[143]	GA (NSGA-II) Pareto front Constrained optimisation	■				Comfort: IEQ cost (k£) + PPD (%) Cash Payback period (year) EI: Carbon payback period LCA (year)	Window-to-wall ratio (%) Window: layer N^o, low-e, Alum. therm. break frame External wall and floor insulation panel type	Paybackcash <30 Paybackcarbon <30	N/A		■	EnergyPlus	MATLAB
[130]	GA (NSGA-II) + ANN (multilayer feed-forward) Pareto front Aggregating method (Weighted sum approach) Penalty Function Method: constrained opt.	■				Energy consumption (kWh/m^{2}year) Thermal comfort (hours): Isum	Roof and external wall thermal conductivity (W/m.K) and volumetric specific heat (kJ/m^{3}K)	Isum (^{o}CH): summer comfort index	N/A		■	TRNSYS	GenOpt (penalty function)
[144]	GA + Exhaustive search method Aggregating method (Weighted sum approach) Sensitivity analysis Non-stationary penalty function method		■	■		Energy savings (kWh/year): sum of average annual energy savings Payback period (months)	Lighting system: energy efficient, motion sensor HVAC system type and power factor correction Water efficient fixtures Energy management and control systems	NPV Payback period Initial investment Energy target		■		N/A	N/A
[87]	GA (variant of NSGA-II) + ANN (Multilayer feed-forward model) Pareto front	■	■		■	Energy consumption (kWh/m^{2}year): sum of energy demands (QHEAT+QCOOL+QSHW) Retrofit cost (€): sum of retrofit actions costs Thermal discomfort (% discomfort hours): PMV	Roof and external walls insulation materials type Window type: Layer N^o, void gas, coating Solar collector type HVAC system type	N/A	LHS		■	TRNSYS GenOpt	MATLAB (model-calibration + neural network + gamultiobj)
[136]	GA (NSGA-II) Pareto front	■	■			Energy consumption (kWh/m^{2}year) Health impacts from exposure to indoor heat, cold and $PM_{2.5}$ (year)	Roof, walls insulation density and conductivity Roof plaster solar radiation absorption coefficient Shading: window blinds (on/off) Kitchen exhaust fan: ventilation rate variation (m^3/s) Envelope air tightness (m^3/m^2/hr)	N/A			■	EnergyPlus	MATLAB Toolbox: gamultiobj function
[145]	GA (NSGA-II) Pareto front Constrained optimisation	■	■	■	■	EI: CO_2 emissions Retrofit cost (€): Construction cost (supply of materials + installation labour + contractor's preliminaries, overheads, profit and contingency) Thermal discomfort (hours/year)	External walls insulation type (int/ext) and thickness Window type: layer N^o+ shading (louvers/overhangs) Infiltration (ACH - Air changes per hour) Ground floor thermal mass options Window-to-wall ratio (%) HVAC system options and setting points Renewable energy: PV s., solar thermal, wind energy	Thermal comfort CO_2 emissions	N/A	■		DesignBuilder EnergyPlus	jEPlus DesignBuilder
[69]	GA + simplified degree-days method	■	■		■	Payback period (years)	Roof, external wall insulation thickness (m), U-value	Capital investment	N/A		■	N/A	N/A

						EI: CO_2 emissions (kg/year) Cost of energy consumption (€): Thermal fuel consumption (kWh) + unit cost (€/kWh)	Boiler type: gas condensing, oil, heat pump, biomass Window type: void gas, layer N^o, glass thickness Envelope air tightness (m^3/h.m^2 @ Pa)	cost					
[140]	GA (NSGA-II) + Analytic hierarchy process Pareto front Quality Function Deployment Model Constrained optimisation	■	■		■	Operational energy consumption (kWh/m^2year) EI: GWP (annual CO_2e + embodied emissions) Retrofit cost (€): initial investment cost	Roof, external walls and floor insulation type Window type: void gas, low-e, U-value (W/m2K) Envelope air tightness (m^3/h.m^2 @ Pa) HVAC system type	Envelope Insulat. Energy consumpt. Env. Air leakage IAQ & Th.Comfort	N/A		■	Excel VBA	N/A
[146]	GA (NSGA-II) Pareto front Sensitivity analysis: stepwise regression Constrained optimisation	■	■	■		Energy consumption (kWh/year): heating, cooling, artificial lighting Retrofit cost (£): initial investment cost	HVAC system options and set points Window-to-wall ratio (%) and building orientation Hours of the day (summer/winter) Walls, ceiling-floor type: heavy, medium, light weight	Thermal comfort <20% of PPD for no more than 150 working hrs/yr	N/A		■	EnergyPlus R statistical software	N/A
[123]	GA (variant of NSGA-II) Pareto front Constrained optimisation	■	■	■	■	HVAC primary energy consumption (kWh/m^2a): sum of energy demands (space heating and cooling)/Conditioned building area Thermal discomfort (% discomf. Hrs): PMV, PPD	Roof solar radiation absorption coefficient Roof and walls insulation thickness (cm)(W/m^2K) Mechanical ventilation system installation (Y/N) HVAC type and set point temperature: standard, condensing, air-cooled, water-cooled Window type: layer N^o, low-e coating	Budget (IIC)	N/A		■	EnergyPlus	MATLAB
[88]	GA (NSGA-II) Pareto front Constrained optimisation	■				Total retrofit cost (€): construction materials + operational phase electricity consumption EI: energy consumption and operation, manufacture of construction materials (EI99)	External walls thermal conductivity (W/m.K) and volumetric specific heat (kJ/m^3K)	Insulation materials thickness	N/A		■	EnergyPlus	jEPlus+EA
[147]	GA (NSGA-II) + exhaustive search method Pareto front	■				Energy demand (MWh/year): heating Retrofit cost (k£): initial investment cost	Loft and walls insulation thickness (mm) Window type: glazing layer N^o	N/A	N/A		■	EnergyPlus	jEPlus
[134]	GA (NSGA-II) Pareto front	■				Energy demand (kWh/year) (heating + cooling) Retrofit cost (€): sum of retrofit actions costs	Roof and external walls insulation U-value (W/m^2K) Window type (layer N^o, frame) and shading type Window-to-wall ratio (%)	N/A	N/A		■	N/A	N/A
[76]	GA (NSGA-II) + ANN (multilayer feed-forward) Pareto front Sensitivity analysis Meta-model based on sensitivity analysis	■	■			Energy consumption (kWh/year) Health impacts from exposure to indoor heat, cold and $PM_{2.5}$ (year)	Roof and external wall insulation thickness (m), conductivity (W/m.K) and density (kg/m^3) Floor insulation (m; W/m.K) + area variation Window type: layer N^o and shading type: overhang External plaster solar radiation absorption coefficient Window-to-wall ratio (%) and building orientation Envelope air tightness (m^3/h.m^2 @ Pa) Kitchen exhaust fan: ventilation rate variation (m3/s)	N/A	LHS	■		EnergyPlus MATLAB	MATLAB (Neural network toolbox + gamultiobj function)
[10]	GA (NSGA-II) + Mersenne-Twister pseudo	■	■			Energy consumption (kWh/m^2year): heating	Roof, external walls, floor insulation thickness (cm)	N/A	Sobol		■	TRNSYS	MATLAB

	random generator Pareto front					Total retrofit cost: NPV (k€) (ICC + annual running costs + replacement cost + residual value) Thermal discomf. (Kh): Weighted Discomf. Time	Window: layer N^o, aluminium thermal break frame Boiler type: standard, modulating, condensing Mechanical ventilation system installation (Y/N)		seq.				
[117]	GA (NSGA-II) Pareto front Constrained optimisation	■	■			Energy consumption ((kWh/m^{2}year): heating Retrofit cost: NPV(k€) (IIC + annual running costs + replacement cost + residual value) Thermal discomf. (Kh): Weighted Discomf. Time	Roof, external walls, floor insulation thickness (m) Window type: layer N^o, SHGC, low-e, void gas Boiler type: standard, modulating, condensing Mechanical ventilation w/ heat recovery system instal.	Incentive rate	Sobol seq.		■	TRNSYS	MATLAB
[148]	GA (NSGA-II) + Mersenne-Twister pseudo random generator Pareto front	■	■			Primary energy consumption (kWh/m^{2}year): heating Retrofit cost: NPV (k€)	Roof, external walls, floor insulation thickness (m) Window type: frame, glazing layer N^o (W/m^{2}K) Boiler type: modulating, condensing Mechanical ventilation w/ heat recovery system instal.	N/A	Sobol seq.		■	TRNSYS	MATLAB
[149]	GA (NSGA-II) Constrained optimisation		■	■	■	Environmental impact (EI): greenhouse gas Emissions (GHG); refrigerant impacts; mercury-vapour emissions; light pollution; water consumption Retrofit cost ($): energy and water fixtures and equipment; management of solid waste; achieving selected LEED-EB credit areas Number of earned LEED-EB points	LEED-EB credit areas: sustainable sites; water efficiency; energy and atmosphere; materials and resources; IEQ; innovation in operation; energy and water consumption fixtures: light fixtures; motion sensors; HVAC system; water heaters; vending machines; hand dryers; solar collectors; solar inverters; other devices (water cooler) Management of solid waste	Light luminance HVAC system Water heating PV system	N/A		■	eQuest	N/A
[138]	GA (NSGA-II) + Artificial Neural Network (ANN) Multilayer feed-forward model ANN Training algorithm Levenberg-Marquardt Pareto front	■				Heating load (kwh) Thermal discomfort (hours above 25^{o}C) LCC of roof and external walls retrofit (€)	Roof and external walls U-value (W/m^{2}K) Window type: U-value and G-value (%) Air change rate (1/h)	N/A	LHS		■	DesignBuilder EnergyPlus	MATLAB Toolbox (ANN+NSGA-II) Excel VBA (LCC)
[105]	GA (variant of NSGA-II) Monte Carlo framework for sampling Sensitivity analysis: Standardised Rank Regression Coefficient Smart exhaustive sampling Pareto front Constrained optimisation	■	■		■	Primary energy consumption (kWh/m^{2}a): DHW, space conditioning, fans, pumps, lighting, equipment Retrofit cost (€): initial investment cost (IIC) Global cost (k€): IIC + replacement cost + state financial incentives + operation cost	Window type: layer N^o, void gas, frame, low-e coating Roof and external walls insulation thickness (m), thermal emissivity and solar radiation absorpt. coeff. Solar shading type: interior shading systems, blinds Renewable energy: PV system, solar thermal HVAC type: natural gas, condensing gas, air + ground source reversible heat pump, CHP, heat recovery syst, air-cooled MagLev and water-cooled chiller	Budget (IC)	LHS		■	EnergyPlus	MATLAB
[133]	GA (NSGA-II) Monte Carlo method of error propagation for uncertainty parameters simulation Pareto front Constrained optimisation	■	■	■	■	Electric energy consumption (GWh/year) Thermal energy consumption (GWh/year) Retrofit cost: NPV (M€) CO_2 emissions Thermal discomfort (hours)	Window type: standard, high performance Boiler type: standard gas, condensing gas Chiller type: standard electric, high efficiency electric Multi-function electric heat pump (heating + cooling) Building automation control system Fluid distribution syst: standard/ increased insulation Renewable energy: PV s. type, solar thermal s. type Lighting system: standard, low consumption, inverter	Legal limits for renewable energies Administration limits on the minimum % of electric green energy	N/A	■		N/A	N/A

[150]	GA + MS Excel programming Constrained optimisation	■				Retrofit cost (€): retrofit actions execution cost Energy demand adjustment (kWh/m^{2}year) (heating and cooling energy demands)	External walls insulation type (W/mK) + thickness (m) Window type: glazing and frame U-value (W/m^{2}K) Shade factor	Heating/Cooling Insulation materials thickness	N/A		■	N/A	MS Excel solver GA Tool
[71]	GA (NSGA-II) Pareto front Monte Carlo sensitivity and uncertainty analysis	■	■	■		Total exergy destructions (kWh/m^{2}year) Energy consumption (kWh/m^{2}year) (HVAC/DHW generation systems) Thermal discomfort (hours): PMV	Roof, wall and floor insulation type and thickness (m) HVAC system type Window type: layer N^o, void gas, U-value (W/m^{2}K) Sealing options (cracks, joints and holes) Lighting system + electric equipment: energy efficient	N/A	LHS	■		EnergyPlus Python SimLab	jEPlus jEPlus+EA
[11]	GA (NSGA-II) Pareto front	■				EI: Life cycle carbon footprint (kgCO_2/m^2) LCC: materials costs; materials waste + transport + maintenance cost coefficient; heating energy cost; electricity cost (£/m^2/y)	Panel and external wall insulation thickness (cm) Ground floor and ceiling insulation (cm) Window type: concrete frame thermal bridging Window-to-wall ratio (%)	N/A	N/A		■	Sketchup EnergyPlus	jEPlus jEPlus+EA
[12]	GA (NSGA-III): Reference-Point Based Non--dominated Sorting Genetic Algorithm Pareto front	■	■			Energy consumption (kWh/m^{2}year) EI: CO_2 emissions in materials + equip. life-cycle Retrofit cost: Initial investment cost Thermal comfort (% discomfort hours)	Roof, ceiling, floor and ground floor insulation type External walls external and internal insulation type Window type: glazing layer N^o, void gas HVAC system type	N/A	N/A		■	EnergyPlus	N/A
[151]	GA (based on NSGA-II) Brute-force algorithm Pareto Front	■	■		■	Primary energy demand (kWh/m^{2}year): heating energy needs + domestic hot water production - contribution from renewable energy sources Global cost (€/m^2): IIC + MC + RC - residual value + energy costs	Roof, walls, ground floor insulation thickness (mm) Window type: U-value (W/m^{2}C^o) Boiler type: biomass, gas Renewable energy: PV system, solar thermal thermosyphon, solar thermal forced circulation	N/A	N/A	■		N/A	N/A
[152]	GA (MOGA, NSGA-II variant) + ANN (multilayer feed-forward) Regression Coefficient Pareto front Uncertainty and sensitivity analysis	■	■	■	■	Annual primary energy consumption (kWh/m^{2}a) Thermal Discomfort: % of hours on annual occupied hours Global cost (€): initial investment cost + replacement costs – discounted public financial Initiatives + discounted lifecycle operating costs For space heating and cooling + DHW production + Direct electric uses – Operating costs savings due to the energy provided by RES systems	Roof and external walls solar radiation absorption Roof and external walls insulation thickness (cm) Window type: glazing layer N^o Solar shading system installation (Y/N) Free cooling system installation (Y/N) HVAC system set points (heating and cooling) Boiler type: existing non-condensing, condensing Chiller type: air-cooled, water-cooled PV system coverage: 0-100% with a step of 10%	Budget (IIC)	LHS	■		EnergyPlus	MATLAB
[153]	GA (variant of NSGA-II) + smart exhaustive sampling Cost-optimal analysis Pareto front Sensitivity analysis	■	■	■	■	Energy demand for heating (kWh/m^{2}a) Energy demand for cooling (kWh/m^{2}a) Thermal comfort (% discomfort hours)	HVAC system set points (heating and cooling) Roof and external walls infrared emissivity and solar radiation absorption Roof + external walls insulation type and thickness (m) Window type: glazing layer N^o, void gas, aluminium Frame, PVC frame, low-e, solar control coatings HVAC type: condensing gas boiler, Air-source heat pump, ground-source reversible heat pump, air-cooled	DH < DH_{BB}	S.E.		■	EnergyPlus	MATLAB

							chiller, water-cooled chiller, efficient gas boiler Renewable energy: PV system						
[106]	GA + Smart exhaustive sampling Cost-optimal analysis Pareto front Sensitivity analysis	■	■			Energy demand for heating (kWh/m^{2}a) Energy demand for cooling (kWh/m^{2}a) Under different climatic scenarios (global warming Neglected, low global warming, medium global Warming and high global warming)	Roof and external walls infrared emissivity and solar radiation absorption Roof + external walls insulation type and thickness (m) Window type: glazing layer N^o, void gas, low-e, alum. frame, PVC frame, selective coatings HVAC type: natural gas boiler, electric air-cooled chiller, natural gas condensing boiler, energy-efficient elec. air-cooled chiller, reversible elec. air-source heat pump, reversible electric ground-source heat pump	N/A	S.E.	■		DesignBuilder EnergyPlus	MATLAB
[154]	GA (NSGA-II) Pareto front	■	■		■	Annual energy savings (€) Retrofit cost: Initial investment cost (€)	External wall insulation thickness (mm) Window type: glazing layer N^o Window-to-wall ratio (%) Lighting system: standard, energy efficient Renewable energy: PV system type Appliances: Fridge class C, energy efficient class A+ HVAC Type: AC unit & electric heater with COP 1 replacement for a heat pump with COP= 4.2	Compliance of Heating + cooling demand Limitation of physical space Technol. capacity Non-negativity nature of variables	N/A		■	EnergyPlus REVIT	MATLAB
[155]	GA Nonlinear integer programming Aggregating method (Weighted sum approach)	■			■	Energy savings (kWh/year): tot. energy consump. pre-retrofit - tot. energy consumption post-retrofit Retrofit cost: NPV ($) Payback period (months)	Roof and external wall insulation materials type ($/m^2) Window type: layer N^o, frame, low-e coating, void gas Renewable energy: Solar thermal panel type	Budget (IIC) Area of solar panel power supply system Measures choice	N/A		■	N/A	N/A
[156]	GA (NSGA-II) + compromise programming Multi Criteria Decision Making method Monte Carlo sensitivity and uncertainty analysis Pareto front Constrained Optimisation	■	■	■	■	Exergy destructions (kWh/m^{2}year) Thermal discomfort (hours): PMV Retrofit cost (£): NPV (50 years)	Roof, wall and floor insulation type and thickness (cm) HVAC system type and set-points control measures: condensing gas, condensing, oil, electric, biomass, district system, ground source heat pump, air source heat pump, PVT, heat recovery system, Micro-CHP with Fuel Cell + electric boiler, ASHP-VRS Window type: layer N^o, void gas, U-value (W/m^{2}K) Sealing options (cracks, joints and holes) Lighting system + electric equipment: energy efficient Renewable energy: PV system, wind turbine Envelope air tightness (ACH 1/hr)	Budget (IIC) Discounted Payback (years) Discomfort hours	LHS	■		EnergyPlus Python SimLab	ExRET-Opt jEPlus jEPlus+EA
[22]	GA (NSGA-II) Pareto front	■	■	■	■	Energy consumption (kWh/m^2-year) Thermal discomfort (hours): PMV Retrofit cost (£): NPV (50 years) Exergy destructions (kWh/m^{2}year) Exergoeconomic cost-benefit 50 years (£/h)	Roof, walls, ground floor, basement wall, pitched roof insulation thickness (mm) Envelope air tightness (ach) HVAC type: condensing gas boiler, oil boiler, electric boiler, biomass boiler, district system, ground source heat pump, air source heat pump, heat recovery System, Micro-CHP with Fuel Cell	Budget (IIC) < 417,028 £ Positive NPV/DPB <50 years Discomfort h < 853	N/A		■	EnergyPlus Python SimLab	jEPlus jEPlus+EA

							Window type: glazing layer N^o, void gas, U-value Lighting type: energy efficiency Renewable energy: PV system type, wind turbines HVAC control system set points (heating)					
[132]	GA (NSGA-II variant) Pareto front Cost-optimal analysis Smart sampling	■	■	■	■	Energy demand (kWh_p/m^2a) Thermal comfort (% discomfort hours): PMV	External walls and roof plaster solar radiation absorption coefficient and infrared emissivity Roof and external walls insulation thickness (mm) HVAC control system set points HVAC type: gas boiler, condensing gas boiler, air--source heat pump, ground-source reversible heat pump, efficient air-cooled chiller, DHW system efficiency: gas boiler Renewable energy: PV system type Window type: glazing layer N^o, void gas, PVC/ wooden frames, low-e/tinted/selective coating	$DH < DH_{BB}$ Heating set point < 22^{o}C	N/A	■	EnergyPlus	MATLAB
[127]	GA (NSGA-II) + Analytic hierarchy process NSGA-II in C original implementation Pareto front	■	■			Energy demand (kWh/m^2year): heating + cooling Thermal comfort: Mean absolute PMV Conservation compatibility (score)	Roof and walls int + ext insulation thickness (cm) Envelope air tightness ($m^3/h.m^2$ @ Pa) Window type: layer N^o, U-value, VT, G-value, void gas Air change rate (1/h) and cooling system (Y/N)	N/A	N/A	■	EnergyPlus	C programming
[109]	GA (NSGA-II variant) Pareto front Smart exhaustive sampling Cost-optimal analysis	■	■	■	■	Energy demand (kWh_p/m^2a): heating + cooling Thermal discomfort (annual % hours) Global costs: IIC + OC + Rd + GHG emissions cost + residual value (€/m^2) GHG Emissions (CO_2 eq)	Walls and roof insulation thickness Walls and roof thermal emissivity and solar radiation absorption Window type: low-e/selective coating, glazing layer N^o, void gas, aluminium/PVC frame, U-value, SHGC HVAC system energy efficiency: reversible air-source electric heat pump, natural gas boiler, condensing natural boiler, air-cooled electric chiller HVAC set point temperature for heating and cooling Renewable energy: PV system type Shading system type and position	Global costs GHG emissions	MATLAB	■	DesignBuilder EnergyPlus	MATLAB
[157]	GA (NSGA-II) Pareto front	■				Energy demand for heating (kWh/m^2year) Energy demand for cooling (kWh/m^2year) Exergy need and exergy available (kWh/m^2year)	Roof and external walls insulation thickness (cm) Roof skylight and window type: U-value (W/m^2K)	N/A	N/A	■	EnergyPlus	jEPlus jEPlus+EA
[158]	GA (NSGA-II) Pareto front Sensitivity analysis for calibration process	■	■			Energy consumption: heating+cooling (kWh/year) Thermal discomfort (annual total hours): PPD Retrofit cost: investment cost (€)	External walls and roof insulation type Window type: glazing layer N^o, void gas, low-e, selective coatings HVAC set points	N/A	N/A	■	IDA ICE	MOBO
[159]	GA (NSGA-II) Pareto front Cost-optimal analysis	■				Energy consumption (kWh/m^2year) Global cost (€/m^2) Energy demand (heating + cooling) Investment cost (€/m^2)	Walls internal and external materials type Walls insulation thickness (cm) and U-value (W/m^2K) PCMs thickness, peak melting t^o, melting t^o range, latent heat of fusion, thermal conductivity Window type: U-value window + frame, glazing layer N^o, void gas, coating low-e, selective Solar shading system	PCM properties (melting t^o range)	N/A	■	EnergyPlus	Python

[107]	GA Nonlinear mixed-integer programming Aggregating method (Weighted sum approach) Sensitivity analysis	■	■		■	Energy savings (MWh) Payback period (months)	Roof and external walls insulation thickness (m) Roof and external walls insulation materials type Window type: glazing layer N^o, void gas, low-e, Aluminium frame, metallic frame HVAC type: chiller and heat pump efficiency Lighting system: energy efficient Renewable energy: PV system type	Budget (IIC) Physical limits (PV installation area, boundary on design variables) EPC rating limit	N/A	■		N/A	N/A
[128]	GA Aggregating method (Weighted sum approach)	■	■		■	Energy savings (MWh/year) Payback period (months)	Roof and external walls insulation materials type Window type: glazing layer N^o, void gas, low-e, metallic frame HVAC type: chiller and heat pump efficiency Lighting system: energy efficient Renewable energy: PV system type	Budget (IIC) EPC rating limit Physical limits (PV installation area, boundary design variables)	N/A	■		N/A	N/A
[135]	GA (based on NSGA-II) Pareto front	■		■	■	Carbon emissions (CO_2/year) Thermal discomfort (hours/year)	Roof and external walls insulation thickness (mm) Envelope air tightness Lighting system: power density HVAC fuel type (gas, biomass) Renewable energy: PV system type Room set temperature Clothing level	Discomfort hours	N/A	■		EnergyPlus	jEPlus+EA
[160]	GA + Mixed integer linear program Pareto front	■	■		■	Total costs: IIC + OC CO_2 emissions: embodied emissions + Operational CO_2 emissions	Walls, roof and floors insulation thickness (U-value) Envelope airtightness (ACH 1/hr) Window type: U-value Systems capacity: Heat pump, gas boiler, electric heater, storage tank diameter, thermal energy storage, borehole heat exchanger length Renewable energy: solar collector + PV area Hourly schedules for technologies	Operation levels	N/A			3D CAD EnergyPlus	N/A
[20]	GA (NSGA-II) Pareto front	■	■	■		Energy consumption (kWh/year) LCC (CAD$ M) Environmental impact: LCA (kg. CO_2 eq.)	Roof and external walls materials and insulation type Roof solar radiation reflectance and emissivity Window type: aluminium, wood and UPVC frame, glazing layer N^o, shading fixed/adjustable Window-to-wall ratio (%) Façade type options HVAC system type (energy efficient) and set-points control measures Lighting system: energy efficient, control settings Renewable energy: PV system type in roof, BIPV Ventilation: Mechanical ventilation system installation (Y/N), natural ventilation, envelope air tightness (ACH)	Budget Owner's preferences Certificate specifications TEC + LCC Boundaries	N/A		■	REVIT DesignBuilder	DesignBuilder
[110]	GA (NSGA-II, NSGA-III Reference-Point Based Non--dominated Sorting GA) Pareto front	■	■			Energy consumption: heating + cooling + lighting + appliance use CO_2 emissions Retrofit cost: material + equipment + construction Thermal cost: PMV	Roof, external + internal walls, intermediate + ground floor and ceiling insulation materials type Window type: glazing layer N^o, void gas	N/A	N/A		■	EnergyPlus	N/A
[111]	GA (NSGA-II variant)	■	■		■	Primary energy consumption (kWh/m^{2}a)	Roof and external walls insulation thickness (m)	Budget (IIC)	N/A		■	EnergyPlus	MATLAB

	Pareto front					Global costs (€/m^2): IIC + OC + discount rate + + residual value of retrofit measures at the end of the assessment period (30 years)	Roof plaster solar radiation absorption coefficient Window type Solar shading type: internal/external HVAC system efficiency Renewable energy: PV system type in roof and %					
[161]	GA (NSGA-II) Pareto front	■	■	■	■	Primary energy consumption (kWh/m^2a) Global costs: IIC + OC + discount rate + + residual value of retrofit measures at the end of the assessment period (30 years)	Roof and external walls insulation thickness (m) Roof plaster solar radiation absorption coefficient Window type: glazing layer N^o, void gas, low-e, wood/ PVC frame Solar shading type: Y/N; internal/external; manual/ Domotic; low/medium/high reflect/trans shade HVAC system efficiency and type: improved reversible air-source electric heat pump Renewable energy: PV system type in roof and %	Budget (IIC)	N/A	■	EnergyPlus	MATLAB
[162]	GA Pareto front	■	■	■		Retrofit Cost ($): IIC; NPV; saving-to-investment ratio; marginal abatement cost EI: CO_2 emissions reduction	External walls insulation thickness and materials Window type: U-value, SHGC, Visible transmittance Lighting system type: energy, radiant/visible fraction Shading system type: Solar transmittance/reflectance Visible transmittance/reflectance, infrared emissivity	National CO_2 emission reduction target by 2030	N/A	■	DesignBuilder EnergyPlus	Excel VBA
[163]	GA	■	■	■	■	Total energy saving (toe/year) Retrofit cost: LCC	Walls and roof external and internal insulation type Window type: glazing layer N^o, low-e Lighting efficiency: LED, occupancy/counter sensor, Reflector, improvement of exit lighting HVAC: electric heat pump, heat recovery system, high-efficiency transformer Insulation of piping system. Replacement of trap PV system roof installation	Budget limit	N/A	■	N/A	Excel

Table header: Opt. topic: Optimisation topic; Env: Envelope; Sys: Systems; BCS: Building control strategies; RES: Renewable Energy Source; Sampl.: Sampling technique; U.V: uncertainty variables; Y/N: Yes/No; S/M tools: Simulation/Modelling tools; Aux. Opt. tools: Auxiliary optimisation tools.
MOO methods: GA: Genetic Algorithm; NSGA-II: Non dominated sorting algorithm; ANN: Artificial Neural Network; MOGA: Multi-objective genetic algorithm.
Objective functions: EI: Environmental impact; GHG: Greenhouse gas; IEQ cost: Indoor environmental Quality cost (k£); HVAC: Heating, ventilation and air conditioning; LCC: Life cycle cost; QHEAT+QCOOL+QSHW: Space heating+ space cooling+ sanitary hot water systems; EI99: Eco-indicator 99 methodology based on LCA (Life cycle analysis) principles; PPD: Predicted percentage of dissatisfied (%); ICC: Initial investment cost; OC: Operating costs; MC: Maintenance costs; Rd: actualisation factor; RDC: Recycle and disposal cost; LCA: Life-cycle assessment; CO2e units: Equivalent carbon dioxide units; PM2.5: Particulate matter 2.5; Isum: Summer Thermal Comfort Index, defined as integrated discomfort degree for air indoor temperature in summer; NPV: Net Present Value; PMV: Predicted Mean Vote Index; GWP: Global Warming Potential; DHW: Domestic Hot Water. Toe: Tonne of oil equivalent.
Decision Variables: IEQ: Indoor Environmental Quality; CHP: Combined Heating and Power system; VT: Glazing visible transmittance; PVT: Photovoltaic thermal system; ASHP-VRS: Air Source Heat Pump-Variable refrigerant system.
Constraints: PV system: Photovoltaic system; NPV: Net Present Value; IAQ: Indoor Air Quality; DH: Discomfort Hours; DH_{BB}: Discomfort Hours referred to the base building configuration; TEC: Total Energy consumption.
Sampling: LHS: Latin Hypercube Sampling; S.E.: Smart exhaustive research.

6. Discussion and conclusions

6.1. Summary of main findings

This paper provides an overview of the potential of GA-based MOO in supporting the development of retrofitting strategies and the DM process. The methodology and search strategy yielded 57 final relevant primary papers and the data abstraction was synthesised and summarised in both text and table forms. All the objectives set at the beginning of this SR were successfully met throughout the analysis regarding: How GA-based MOO is being applied in building retrofit, which techniques aid its implementation and what type of case studies are being covered; current trends regarding the objective functions explored for optimal trade-offs, as well as the decision variables chosen for optimisation; which simulation-optimisation approach is being implemented and which software tools can be identified as preeminent in GA-based MOO; whether traditional and heritage buildings are being targeted in GA-based MOO retrofit studies, and if so, which objective functions are being addressed and which methods are being used to quantify heritage qualitative concepts. Main findings resulting from these objectives are presented in the summary hereunder:

- Environmental, social and economic sustainability scopes are addressed in most primary studies (PS). While the environmental scope is the most covered, the social scope is found at the opposite end of the spectrum. Case studies are generally real buildings, but simplified building models and Archetype buildings are used as well. Residential buildings are the most explored building use category, followed by educational buildings;
- In GA-based MOO implementation, the Pareto-based optimisation concept is the most commonly used, either by itself or in combination with an aggregating method, amongst which the WSM stands out as most frequently used, followed by AHP and the ε-constraint method. NSGA-II algorithm is the go-to GA for optimising multi-objective problems in building retrofit, either as stand-alone form, as a variant or coupled with other algorithms and techniques. The development of approximation methods through meta-models or surrogate models, such as ANN, is successfully emerging as a method to approximate the pre-established performance functions that describe the objectives without reducing the complexity of the problem. Auxiliary methods such as sampling, uncertainty, and sensitivity analysis have also been used to facilitate the adjustment of parameters and variables toward decreasing the number of required simulations and hence reducing the most consuming GA optimisation stage;
- As for current trends regarding objective functions, energy and retrofit cost linked objectives stand out as the most researched ones, generally within a two-objective optimisation, or in a trade-off analysis with comfort objectives, and less commonly environmental impact. Health and building conservation are found

at the bottom of the objective functions addressed. Decision variables globally fall into four main design categories: building envelope, building systems including heating, cooling and lighting, incorporation of renewable energy technologies into buildings, and building control strategies. The building envelope section makes up for the overwhelming majority of decision variables;

- Little attention has been addressed to buildings owning any heritage, historical or traditional value and protection. Energy savings or higher comfort level objectives are too often obtained at the expense of heritage degradation. The most common objectives for trade-off analysis are linked to retrofit costs, including payback, life cycle cost and cost of energy consumption, along with the environmental impact of buildings. Indoor comfort is found to attract less attention followed by conservation compatibility; the objective functions definition and quantification are especially challenging when objectives are intrinsically qualitative such as aesthetics, urban integration, and conservation compatibility in heritage retrofit. AHP based on the opinions of a team of experts was used to overcome these quantification issues;
- Two main simulation-optimisation approaches were adopted: a dynamic simulation, based either on detailed or simplified models, and a static modelling approach. In the first one, EnergyPlus accounts for more than half of the PS employing an energy simulation engine and is followed by TRNSYS. Regarding optimisation tools, Generic tools are the most adopted ones, in combination with EnergyPlus and TRNSYS, and MATLAB in particular, despite not being specifically designed for building optimisation and requiring a higher expertise level, revealed itself as the optimisation tool of choice. Simulation-based optimisation tools are also used, such as the DesignBuilder’s optimisation module and the jEPlus option. jEPlus+EA, an optimisation engine oriented tool, comes in second place within the most used optimisation tools after MATLAB. A separate optimisation engine oriented tool based on NSGA-II, MultiOpt, is designed specifically for retrofit solutions optimisation. Customised design optimisation techniques were used as well, in particular for introducing energy standards coding into the optimisation process. Static simulation models that are coupled with optimisation techniques are scarcer than dynamic simulation ones.

The following sections focus on the potential of GA-based MOO in supporting the development of retrofitting strategies and the DM process, the robustness of outcomes being achieved, and the major challenges and limitations in its implementation.

6.1.1. Outcomes and potential

Most PS reported finding robust results and successful outcomes regarding the implementation of GA-based MOO in building retrofit. The method was found to be robust in exploring the search space for a wide range of building retrofit MOO problems, in which simultaneously different competing criteria such as energy consumption, thermal comfort, retrofit costs, etc. are taken into consideration; additionally it also demonstrated the ability to lead to sets of more reliable and consistent optimal retrofit solutions, in a reasonable computational time when compared to standard simulation-based or exhaustive search approaches. Significant improvement of objective functions with reference to baseline was reported. Outcomes further established the value of using constraints in MOO and the need to account for uncertainties in order to achieve robust-optimal solutions.

Moreover, the outcomes reveal that GAs coupled with dynamic thermal simulation allows for a more relevant discussion and extrapolation of the developed method. Yet it is also argued that coupling GAs with static simulation modelling is a valid combination that allows further accessibility to MOO in building retrofit without the requirement of high-end computational resources. In addition, the significance of GA-based MOO for solving building retrofit problems was enhanced through the comparison of mono-objective optimisation and MOO outcomes in several of the PS, concluding on the restrictive character and limited Pareto front findings of mono-objective optimisation for the DM process: in contrast, the thorough knowledge of trade-offs between competing objectives in MOO was found to support the DM process and the development of robust retrofit strategies, allowing decision makers to understand what is at stake and providing them with the flexibility to select the best compromise solutions. This is especially relevant regarding cost objectives, as the method showed the potential to avoid choosing financially infeasible options. The outcomes of using aggregating methods in the Pareto-based optimisation studies, most commonly WSM, were displayed as effective; its beneficial impact in the DM process is accentuated, through the tuning of weighting factors and selection of the Pareto front solution set. As aforementioned, NSGA-II was the go-to GA for MOO in building retrofit in PS and its efficiency and reliability have been shown in MOO and building performance simulation problems. That said, for a fair amount of PS, results also indicated that yielding optimal retrofit solutions required GA-mixed techniques and in a few cases a modified GA, due to time-consuming and effectiveness challenges. These underlying issues are addressed in additional detail in the following section. The outcomes of GA-mixed techniques were favourable in all PS where it was implemented, and its efficacy, accuracy, and performance was emphasised. ANN, in particular, proved useful as an approximation method for complex functions and, after being properly trained, was able to replace annual computer simulations. Implementing ANN inside NSGA-II enabled faster evaluations and in a number of instances, the time saving associated with it was so significant that the optimisation process would not have been feasible without it. Furthermore, the small number of GA-based hybrids implemented in the PS was found to be more computationally effective and yield more solution satisfaction than stand-alone GA.

The results of this SR point to the need to employ GA-based MOO techniques for the whole building retrofit project process. While the robust evaluation of GA-based MOO efficiency needs further research, it can be stated that overall there is great potential in this optimisation method to support the development of retrofitting strategies and the DM process in building retrofit, given that it is complemented with auxiliary tools and techniques. The robustness of the method is further discussed in the following section.

6.1.2. Challenges and limitations

Several challenges are worth mentioning as they systematically came up regarding the implementation of GA-based MOO in building retrofit.

The most common one and often pinpointed as the major drawback associated with GA implementation would be the time-consuming feature of its optimisation. As previously mentioned, time costly simulation evaluations for reaching optimal solutions can turn out to be infeasible, especially when applied directly to big and complex models and over extended periods of time. In order to avoid resorting to very simplified models, which can lead to oversimplification and inaccurate modelling, several strategies were implemented in the PS to overcome time-consuming computational issues. Among these, the development of approximation methods through meta-models or surrogate models, such as ANN, stood out as a method to approximate the pre-established performance functions that describe the objectives without reducing the complexity of the problem. Although not without its difficulties, as it requires a significant amount of data for training in order to reach accuracy and some objective dependent accuracy issues were reported in a couple of studies, ANN was found to significantly reduce computational time of GA-based MOO. Parallel computing and simulation server services were also employed favourably. Furthermore, the analysis performed in this SR also highlights how crucial the identification of optimal computing settings is to improve both time and accuracy in the optimisation process; for this purpose, auxiliary methods such as sampling and sensitivity analysis facilitated the adjustment of parameters and variables toward decreasing the number of required simulations and hence reducing the most consuming GA optimisation stage. Moreover, a minority of the PS modify NSGA-II or resort to a hybrid GA technique to surpass effectiveness issues. Other algorithms were used in combination with GA in order to compensate for its shortcomings regarding the random initial population selection. In addition, when solving a MOO using four or more objectives the convergence performance of GA was found to be diminished and a reference-point based non-dominated sorting genetic algorithm (NSGA-III) was developed for higher efficiency.

The interpretation of the Pareto front and selection between the Pareto optimal solutions showed up regularly as an added challenge. Its wide variety is both an advantage and difficulty in DM, as the establishment of final selection criteria among all the recommended retrofit actions can be complex. A wide assortment of non-systematic techniques, thresholds, and MCDM were adopted to solve it, tuned for specific application, amongst which are: weighted systems (WSM, AHP) resulting in a final solution heavily dependent on the chosen weights, LCC and LCA, minimisation of global retrofit costs, payback period, thresholds regarding comfort or heating and cooling load, and conservation compatibility as final criteria for choosing between the retrofit solution sets identified. The lack of a standard systematic approach is evident at this stage, as well as throughout the whole GA-based MOO approach and it embodies both a challenge and limitation as well. As seen in the analysis section, the approaches, tools selection and coupling being employed are quite scattered. Setting systematic flexible frameworks for performing MOO for decision support, i.e. with a common core methodology while still flexible enough to adapt accordingly to the specificities of each case, rather than ad-hoc approaches, would be beneficial to increase its acceptance and frequency of use, as well as application efficiency and regulation, while helping reverse its lack of awareness and trust in results in retrofit practice.

In addition to the task of interpretation of results, a high level of expertise is needed to perform and understand the whole MOO process, as well as manage and combine specialised software. Switching between the modelling and optimisation environments can be complex and susceptible to mistakes, requiring at times that a coupling function be written to achieve communication between environments. A few of the PS stress this limitation and consequently develop methodologies based on more accessible software that require no previous knowledge of MOO. These models tend to only be applicable to each particular case and would have to be changed for another case study analysis.

The objective functions definition and quantification was also found to arise as a predicament, in particular when the objectives in question are intrinsically qualitative such as aesthetics, urban integration, and conservation compatibility in heritage retrofit. To overcome quantification issues, the AHP method previously described was used, requiring the opinions of a team of experts. Nonetheless, this method comes with its own challenges linked to scepticism, inconsistencies and the required understanding of all parameters on the experts' end.

Some potential limitations regarding the robustness and reliability of the studies outcomes can also be pointed out. Sampling for DM needs to be representative for results to be considered robust enough (e.g. when using AHP based on experts). A high level of simulation model input uncertainty (e.g. savings estimation, retrofit actions costs data, insulation cost, energy cost, inflation rate, emissions data, environmental conditions, material variability, model assumptions, constraints uncertainty, etc) was regularly reported. The lack of monitoring for the majority of the PS increases output uncertainties. Also, had more studies included a pre and post intervention monitoring as a results validation scheme, more robust conclusions could have been drawn. Where uncertainties were taken into consideration, its impact on the optimisation process and the ability to achieve robust solutions were emphasised: a clear shift of the Pareto front was described in the few PS taking the uncertainty of the main parameters used in the building model into account. Understanding and systematically considering uncertainty in the optimisation process would add further robustness to findings and help breach any potential inadequacy in results. As aforementioned, optimisation results are also affected by the use of simplified models. Often, custom simplified thermal models were developed instead of using detailed BPS software and this conveys that their results and conclusions were only valid for each case in particular. Furthermore, some tools developed for the studies are not, at the time of this SR, fully validated yet. The objective function definition is a vital part of the optimisation process and must be carefully performed, as suboptimal solutions could be generated depending on this. The need to expand both objective functions and design variables was acknowledged in nearly each of the PS, yet the influence of occupants' behaviour on the cost, energy and comfort-optimal solutions are important parameters that were scarcely considered. Some studies could also benefit from constraints inclusion (e.g. indoor thermal comfort, indoor air quality, renovation time, compliance with regulations).

6.2. Gaps in knowledge and suggestions for further work

6.2.1. Gaps in knowledge and future research needs

This SR revealed some gaps in the available literature and that more research is needed. The latter would ideally provide solutions to the limitations and challenges described in section 6.1.2. and help build trust in MOO results, further adding to its popularity in research and incorporation into practice. Suggestions for future work regarding GA-based MOO in building retrofit were identified and classified under two main categories: Method and tools, and topics lacking research. The items in the first category are listed as follows:

- Development of a standard systematic yet flexible method for the whole GA-based MOO implementation;
- Development of seamless link between optimisation and simulation, with open source environments;
- Incorporation of optimisation into already well-known and used BPS and conventional design tools, bridging the gap between research and practice**;**
- Development of an environment with a friendly GUI;
- Development of standard systematic solution ranking methods for post-optimisation;

- Further research on NSGA-II's performance, efficiency, and accuracy, regarding, in particular, the initial population selection and population diversity, shortcomings in the iterative process and convergence performance for more than four objectives;
- Further research on the approximation accuracy and efficiency of surrogate models, such as ANN, and its impact on GA-based MOO;
- Agile and systematic integration between GA and approximation methods;
- Systematic incorporation of uncertainty into the MOO process;
- Further research including pre-intervention monitoring for MOO input data, as well as post-intervention monitoring;
- Further research on the objective function quantification and definition process;
- Further research on sensitivity, uncertainty analysis, and sampling tools in relation to building retrofit MOO.

The following topics were identified as needing future research:

- Environmental and social sustainability scopes addressed jointly in GA-based MOO;
- Building retrofit MOO in general;
- MOO in retrofit of Historical, traditional and special architectural value buildings, in particular incorporating the quantification of qualitative parameters regarding aesthetics and conservation;
- Objective functions expansion concerning: occupants behaviour, health, building conservation, retrofit costs including replacement costs and life-cycle cost, visual and acoustic comfort, indoor environmental quality, environmental impact including Life cycle carbon footprint, economic feasibility, building performance degradation and exergy;
- Design variables expansion concerning: building control strategies, solar shading, lighting system, renewable energy technology in buildings namely wind power and solar thermal forced circulation;
- MOO including constraints such as indoor air quality, retrofit time, compliance with regulations, energy consumption, CO_2 emissions and insulation materials properties;
- Impact of weather files in GA-based MOO robustness;
- GA-based MOO considering the retrofitted building performance over its lifetime and its ability to adapt to climate change, built on future weather files.

6.2.2. Bridging the gap between research and practice

Filling some of the aforementioned breaches could strongly contribute to bridging the gap between research and practice regarding the use of GA-based MOO for building retrofit problems, namely: reducing the lack of confidence and awareness on the use of optimisation through more robust research, developing a standard systematic method for the whole GA-based MOO implementation, seamlessly linking optimisation and simulation with open source environments, incorporating optimisation into already well-known and used BPS and conventional design tools and developing a friendly GUI environment. Along with these, a vigorous and sustained educational effort would be crucial to assure the understanding of the optimisation process, concepts and software management.

The regular adoption of GA-based MOO in practice could significantly impact the way buildings are retrofitted, with the benefit of assessing a building in its pre-intervention state, as well as evaluating a large number of retrofit options and clearing hesitations by facilitating informed design decisions. It would also provide designers with overcoming the issues of conventional and parametric processes. Limited resources are a very relevant factor for retrofit projects in practice and the fact that this method allows for the identification of the most cost-effective measures can translate into attracting more investment for similar retrofit projects. Likewise, it could lead to more appropriate decisions in heritage retrofit by introducing an approach based on the integrated decision process between designers and the heritage authority. Finally, it is important that moving forward with optimisation in practice, design teams do not undermine the retrofit process by starting to solely rely on the optimisation technique but still build on the fundamental social and cultural parameters and find ways to incorporate these more qualitative criteria into the method.

6.3. Strengths and limitations of the study

The methodology used in this SR was appropriate to review the available research evidence and answer its focused research question. It was conducted based on a predetermined protocol, the PRISMA statement approach, and a comprehensive search strategy maximising the identification of all potentially relevant information was described. Important sources of information other than peer-reviewed papers were not overlooked, as conference proceedings and books were considered for screening. Narrow study inclusion and exclusion criteria and their justification were outlined in detail. These criteria are pertinent to the research question and were set with no a priori knowledge of the PS, hence avoiding potential bias and allowing for an accurate selection of studies. The same four phases protocol was followed for each primary study: identification, thorough two-level screening, eligibility, and inclusion. All decisions regarding information compilation were disclosed to the best of the authors’ abilities. The data abstraction from each primary study was rigorous as well as reproducible and the information was appropriately synthesised and summarised by using both text and tables. It presented the range of approaches that are being taken and the heterogeneity between PS was explained. Furthermore, one can state that this SR contributes to the problem solution as it was established whether scientific findings are consistent and generalizable, gaps in available literature were identified and practical recommendations were generated.

Even though a comprehensive search of available literature reduces the possibility of publication bias and makes it unlikely that relevant studies were missed, one cannot exclude the possibility that some potentially eligible publications might have been missed. The PS included were inevitably diverse in their design, methodological and detail quality and evidently this SR conclusions are only as reliable as the methods used in the PS. Some data was at times unavailable or insufficiently described. A lack of methodological consistency of the PS had an impact on the conclusion drawing process. While primary authors were not contacted to confirm the accuracy of abstracted data, they were contacted when in need of additional details not provided in the primary report, with only one response received. Notwithstanding that no time frame was set and unlimited geographic context was followed, no relevant publications prior to 2000 were found and only English-language records were obtained. The number of PS fitting the inclusion criteria of this SR could see a rapid expansion in the near future due to the topic’s growing popularity.

Declarations of interest

None.

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