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Review Paper

A Systematic Review of Multi-Objective Optimization Methods of Building Energy Performance

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Abstract
In recent years, increasing attention has been given to improving the energy efficiency of buildings in order to reduce their environmental impact and operational costs. As a result, multi-objective optimization methods have become an important tool for optimizing building energy performance. This research reviews building performance analysis approaches in a comparative method and results in a systematic overview of the existing multi-objective optimization methods used in the field of building energy performance. This review covers a wide range of optimization techniques, including genetic algorithms (NSGA-II), evolutionary algorithms, particle swarm intelligence algorithms, and other metaheuristic approaches. Furthermore, the review provides a comprehensive analysis of the strengths and weaknesses of each method in different fields such as daylight, ventilation, and thermal performance analysis. In order to achieve the aims of the research alongside reviewing the Scopus scientific database, various relevant studies were investigated. Eventually, this study provides. Eventually, this review identifies gaps in the literature potential in research directions and proposes multiple ways for future research.

Keywords: *Multi-objective Optimization, Building envelopes, Thermal Performance, NSGA-II, Genetic Algorithm.*

1. INTRODUCTION

In recent decades, computational tools unlocked various potentials to solve complex engineering problems which was not possible with conventional approaches. The parametric simulation method can be employed to improve building performance (Nguyen, Reiter, and Rigo 2014). This approach enables the researchers to test effective variables one by one and observe the end results (Kaastra and Boyd 1996).

The simulation environment brings the advantage of targeting a specific variable in an iterative testing process in order to identify the building element's behavior. This is important as this behavior can be non-linear, multidimensional, and dependent on multiple factors. Parametric methods can be used to achieve an optimal solution by considering multiple factors and handling large amounts of computation using the machine's power. The computer-building model is usually ‘‘solved’’ by iterative methods, which creates an infinite sequence of better approximations toward a solution that satisfies an optimality condition. These methods are often automated through computer programming because of their iterative nature and are commonly referred to as "numerical optimization" or "simulation-based optimization."

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Since the late 1980s and early 1990s, Numerical optimization received significant attention with computer science advancements that have led to mathematical optimization methods (Gallopoulos, Houstis, and Rice 1994). From then, the combination of building energy simulation with algorithmic optimization was studied. However, publishing the studies was started in the late 2000s (Touloupaki and Theodosiou 2017).

The trend continued after 2000 and has grown every year and nowadays it is been utilized in the field of architecture and energy performances. Climate change concerns in recent years and the energy crisis resulted from political conflicts, this trend will continue to grow at least for the upcoming decade. (Figure 1) shows the number of published studies in this field in the Scopus scientific database.

Although building performance analysis with simulation-based optimization algorithms was studied for almost three decades, it has not been reviewed in a comparative model that distinguishes the different optimization algorithms. This paper highlights the features, limitations, advantages/disadvantages of these algorithms as well as their potential applications in building science. The outcome of this overview can guide future research in building performance analysis and optimization.

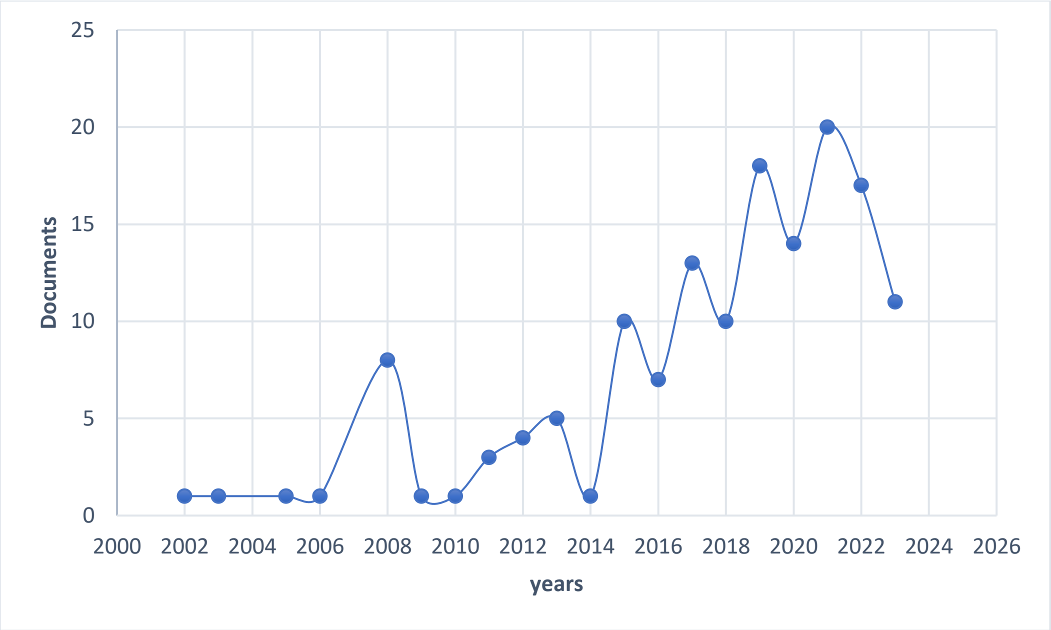

Fig 1. Multi-Objective Optimization and Building Energy based on Scopus scientific database

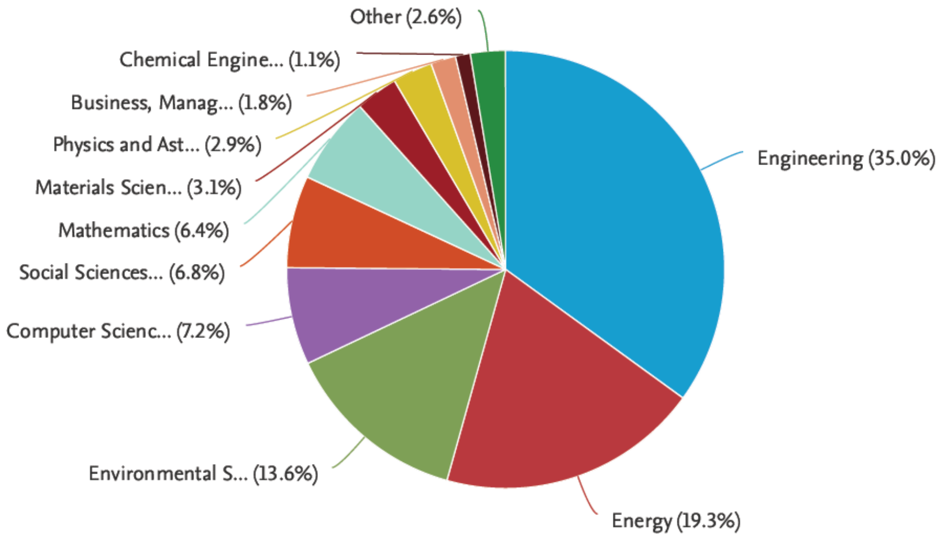

Fig 2. Multi-objective optimization used in several fields on the Scopus scientific database

2. OPTIMIZATION IN BUILDING SIMULATION

The term "optimization" is commonly used to describe the process of making something as efficient and effective as possible, for instance, in the context of a design, system, or decision. In mathematics, statistics, and other sciences, mathematical optimization involves finding the best solution to a problem from a set of available alternatives.

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In building performance simulation (BPS), optimization doesn't always refer to achieving the globally optimal solution(s) to a problem. This is because BPS problems are often complex, and finding all possible solutions may not be achievable. Instead, optimization in BPS generally aims to find feasible solutions that satisfy specific criteria and constraints. However, due to non-linearities inherent in BPS modeling, the exact optimal solution(s) It may not be possible to achieve the desired outcome due to limitations in available resources or time constraints. (Baños et al. 2011).

It is generally accepted within the simulation-based optimization community that the term "optimization" outlines an automated process that relies solely on numerical simulation and mathematical optimization techniques. However, there are studies that have used the term 'optimization' to describe an iterative improvement process that uses computer simulation to achieve sub-optimal solutions (Anon n.d.-j).

Optimization algorithms have been used in building science since the 1960s in order to enhance building performance and reduce costs. With advancements in optimization methods, new algorithms were introduced in the 1970s, and the use of optimization algorithms gained importance in the 1990s with the progress of computer technology (Wang and Zhai 2016).

In the 2000s, optimization algorithms became a key area for improving building performance and lowering energy consumption with the widespread use of intelligent systems. Optimization algorithms are now employed online and in real-time with the development of monitoring and computing device technology, making them a crucial field in the construction industry.

In linear optimization, the objective is only one problem. But in real problems, we may need to consider several issues together to approach the optimal state. For instance, In the field of building design, various topics such as daylight optimization, energy consumption, and natural ventilation are considered. In such cases, different objectives may conflict with each other and optimization of one objective reduces the improvement of other objectives. Multi-objective optimization allows the designer to find the best balance between different objectives among a set of options and, in this way, achieve multiple solutions to the problem that all optimally respond to the desired objectives.

Also, in problems that are non-linear and cannot be simplified to become linear, it is useful to use multi-objective optimization. For example, in building energy optimization, it might be necessary to consider a series of objective variables and find the best balance between them according to the constraints of the problem.

"Computational optimization" in building refers to optimizing the performance of various building systems using computational methods and optimization algorithms (Anon n.d.-d). The goal of optimization in buildings is to reduce energy consumption, (Anon n.d.-f) improve the quality of indoor and outdoor air, lower costs, and enhance the comfort and health of occupants. Building optimization is achieved through the optimization of different building systems such as air conditioning, lighting, water systems, heating systems, energy-efficient systems, and others. These methods employ mathematical models and computer simulations and algorithms such as Genetic or SPE A-2 algorithms to optimize various building systems by using sensor data and environmental information.

2.1. Single and multi-objective optimization

Single-objective and multi-objective are two different approaches in optimization targets same goal (Deb and Deb 2014).

In single-objective optimization, the main goal is to obtain the best value of an objective variable. Given an objective function and a limited set of variables, the goal of single-objective optimization is to find the value of the variables that maximizes or minimizes the objective function. In this method, only one target variable is considered, and to obtain its optimal value, all other variables are assumed to be constant.

But in multi-objective optimization, more than one objective variable is considered, and the goal of optimization is to find a set of variables that simultaneously maximize or minimize all objective variables. In this method, multiple target variables are related to each other, making it necessary to consider all of them simultaneously for optimization. Therefore, to obtain the best solution, all target variables should be considered and optimized simultaneously.

One of the important reasons for using multi-objective optimization is that often in real-world complex environment, problems have more than one objective. For example, in designing a system, several objectives such as performance, cost, and safety must be considered simultaneously.

The objectives in solving multi-objective optimization problems are:

To retain non-dominated points in the objective space and their corresponding solution points in the decision space.

To continuously make algorithmic advancements towards the Pareto front in the objective function space.

To sustain a variety of points on the Pareto front and a range of Pareto optimal solutions in the decision space.

To offer decision makers and designers an ample yet restricted selection of Pareto points. (Chiandussi et al. 2012).

In general, multi-objective optimization can be applied both scientifically and practically in numerous fields, including engineering, computer science, building science, and economics, to enhance and optimize various processes and systems (Konak et al) (Konak, Coit, and Smith 2006)

3. MAJOR OPTIMIZATION ALGORITHMS

There are various methods used for multi-objective optimization. Through an investigation of different research studies, it can be concluded that five major optimization algorithms are dominant:

1. Non-Dominated Sorting Genetic Algorithm (NSGA-II)
2. Strength Pareto Evolutionary Algorithm (SPEA-II)
3. Multi-Objective Particle Swarm Optimization (MOPSO)
4. Multi-Objective Differential Evolution (MODE)
5. Multi objective Optimization Evolutionary Algorithms (MOEAs)

3.1. Non-dominated Sorting Genetic Algorithm II (NSGA-II)

A well-liked and frequently used evolutionary algorithm for multi-objective optimization is NSGA-II. Holland created the genetic algorithm (GA) in the 1970s. Darwin's theory of natural selection and Mendel's theory of genetics served as the foundation for this optimization technique. The method is based on "natural selection and survival of the fittest" and is highly parallel, unpredictable, and adaptive (Holland 1992).

The solutions in a genetic algorithm often replace the initial variables with a code. A solution is typically represented by a chromosome, which is a string of bits. Genes are the names for each bit position, and alleles are the values that each gene represents. With advancements in computer technology, genetic algorithms (GAs) are now widely employed in various fields, including pattern recognition, image processing, neural networks, optimal control, and more. The GA has also been used in a number of building studies, including online optimization (Coffey 2008), HVAC system controls optimization (Huang and Lam 1997), and optimization of green building design (Wang, Zmeureanu, and Rivard 2005). hese experiments have proven that GA is quite effective even when dealing with non-differentiable functions. When compared to the baseline scenario, it has demonstrated its effectiveness.

NSGA-II is an evolutionary algorithm. Evolutionary algorithms were created as a solution to the issues that the traditional direct and gradient-based techniques have when dealing with non-linearities and complicated interactions:

- The initial choice of solution determines whether convergence to an ideal solution occurs.
- Most algorithms have a propensity to remain in a non-optimal state (Calle 2017).

Figure 4 provides an illustration of this circumstance. The points that will increase the diversity of the selected points are chosen rather than arbitrarily eliminating some members from the previous front.

NSGA-II is a second-generation genetic algorithm that assesses the population's fitness using a non-dominated sorting technique. Fast non-dominated sorting, quick crowded distance estimation, and a straightforward crowded comparison operator are its three unique specification (Anon n.d.-a). Based on numerous solutions' Pareto-dominancy, NSGA-II assigns them into several non-dominated fronts using a quick and effective sorting technique. To produce new offspring and preserve population variety, it engages in selection, crossover, and mutation processes. The application of NSGA-II to building energy optimization issues has proven successful (Mane and rama narasingarao 2021). The details phases of the Non-dominated Sorting Genetic Algorithm II (NSGA-II) are shown in Fig. 5 (Yusoff, Ngadiman, and Zain 2011)

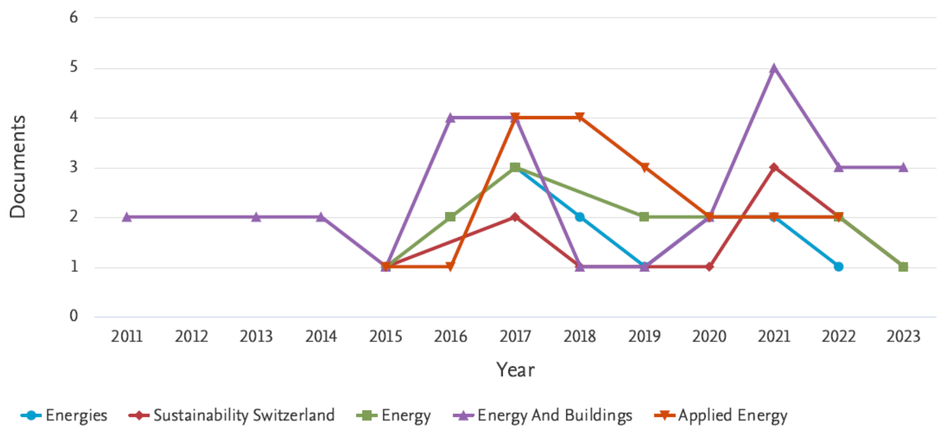

Fig 3. Multi Objective Optimization used in Building Energy field on Scopus scientific database

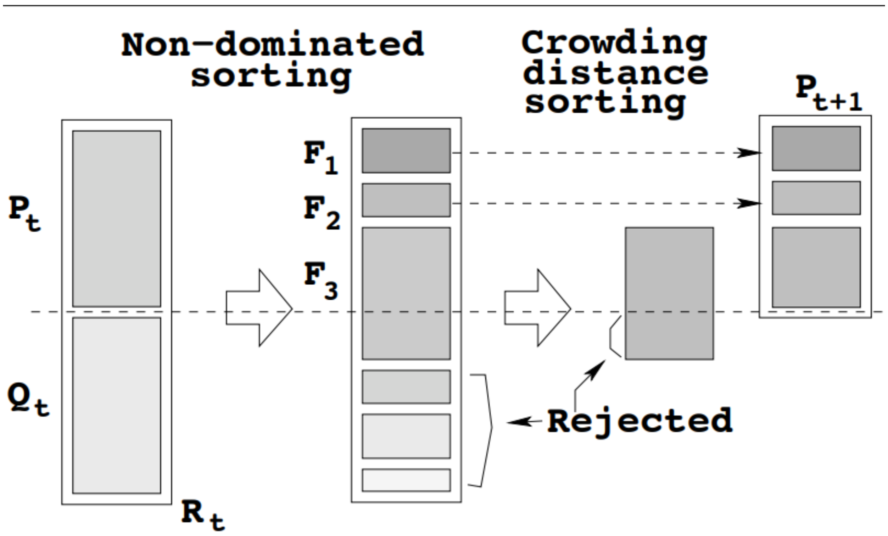

Fig 4. Schematic of the NSGA-II procedure (Deb 2001)

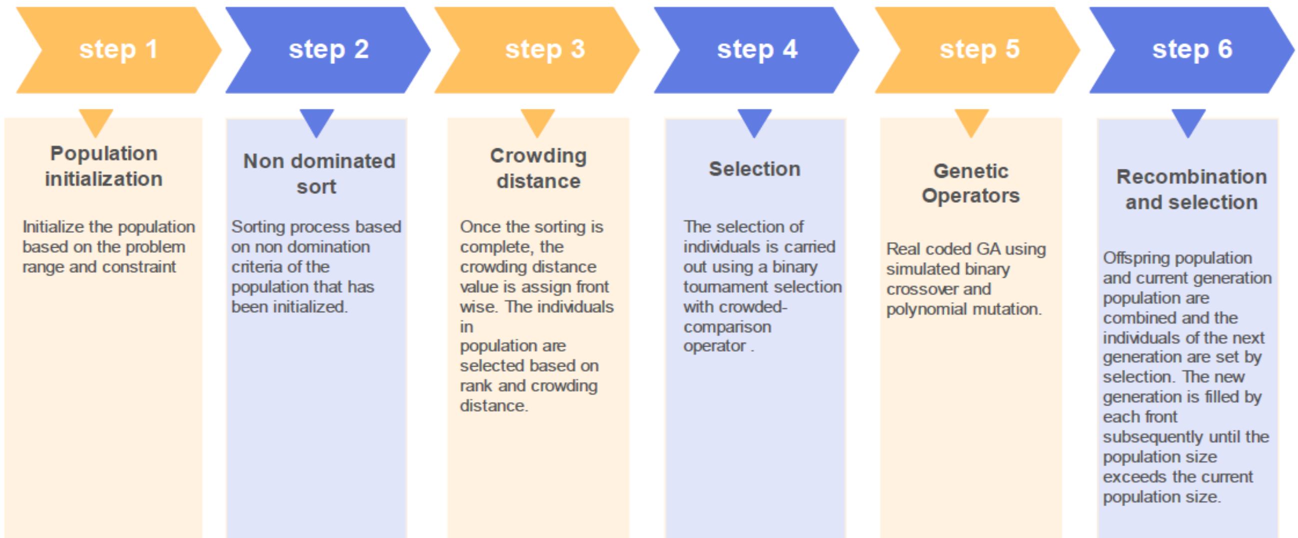

Fig 5. Details steps of Non-dominated Sorting Genetic Algorithm II (NSGA-II) (Yusoff et al. 2011)

3.2. Strength Pareto Evolutionary Algorithm (SPEA-II)

A variety of non-dominated solutions are sought after by the multi-objective evolutionary algorithm SPEA-II. By truncating and managing the archive set, Zitzler's SPEA2 is an improved form of SPEA that can produce an orderly-distributed Pareto solution. (Anon n.d.-i). One effective multi-objective evolutionary algorithm is SPEA, which has a small number of configuration parameters, quick convergence, strong robustness, and evenly distributed solution sets. It has been used in a variety of multi-objective planning domains in both academic and industry settings. SPEA2+ was applied in the quality performance conceptual design domain by Zhe Wei, Yixiong Feng, Jianrong Tan, and others. Effective references can be obtained by the Pareto optimum set based on the fuzzy set theory [8]. However, localized solution sets are a drawback of SPEA2. However, SPEA2's use in DG coordination and optimization in a distribution network is rarely investigated (Wei et al. 2009).

The algorithm keeps track of a population of potential answers and assesses the fitness of each one using both objective function values and density estimates. The density estimates calculate the separation between each solution and its closest population neighbors, and the goal function values show how well each solution performed relative to the various objectives. A two-tiered fitness assignment system, including both raw fitness and environmental fitness, is used by the SPEA-II algorithm. The environmental fitness is determined based on density estimations, whereas the raw fitness is generated based on the number of solutions that dominate a particular candidate solution. While the environmental fitness is used to choose solutions for reproduction, the raw fitness is used to rank the solutions within the population. When replicating, the algorithm (Shi and Lee 2015). Fig. 6 demonstrated the specific steps of the Strength Pareto Evolutionary Algorithm.

3.3. Multi-Objective Particle Swarm Optimization (MOPSO)

Xue and Zhang (Xue, Zhang, and Browne 2013) investigated the use of MOPSO in feature selection problems and suggested two variants of MOPSO called NSPSOFS and CMDPSOFS by incorporating the ideas of crowding, mutation, and dominance for the former and non-dominated sorting for the latter.

Finding a set of non-dominated solutions that represent the Pareto front - the best trade-off between various objectives is the end-goal of MOPSO. Each potential solution is rated according to its quality and diversity using the fitness function employed by MOPSO. A solution's quality is determined by its objective function values, whereas its variety is determined by how far away it is from other solutions in the population (Han et al. 2021).

MOPSO uses a number of operators to update each particle's position and velocity during optimization in order to accomplish the mentioned goal. The global best operator updates a particle's position based on the best-known solution of the entire swarm, while the personal best operator does so based on the particle's best-known solution. Multiple particles are combined by the differential evolution operator to produce fresh candidate solutions that can be utilized to modify the present particle's position (Lalwani et al. 2013).

Additionally, MOPSO employs a method known as crowding distance to keep the population's diversity of solutions. The density of solutions around each candidate solution is measured by crowding distance, which enables the algorithm to concentrate on examining the less-explored areas of the search space (Clarke and McLeskey 2015).

MOPSO has proven to be successful at resolving complex optimization issues with a variety of competing objectives. The technique can handle complex optimization issues and is scalable. However, when dealing with specific sorts of optimization problems, it may experience problems including early convergence, stagnation, and sluggish convergence. The MOPSO algorithm's flowchart, which is based on a dominance criterion, is shown in Figure 7.

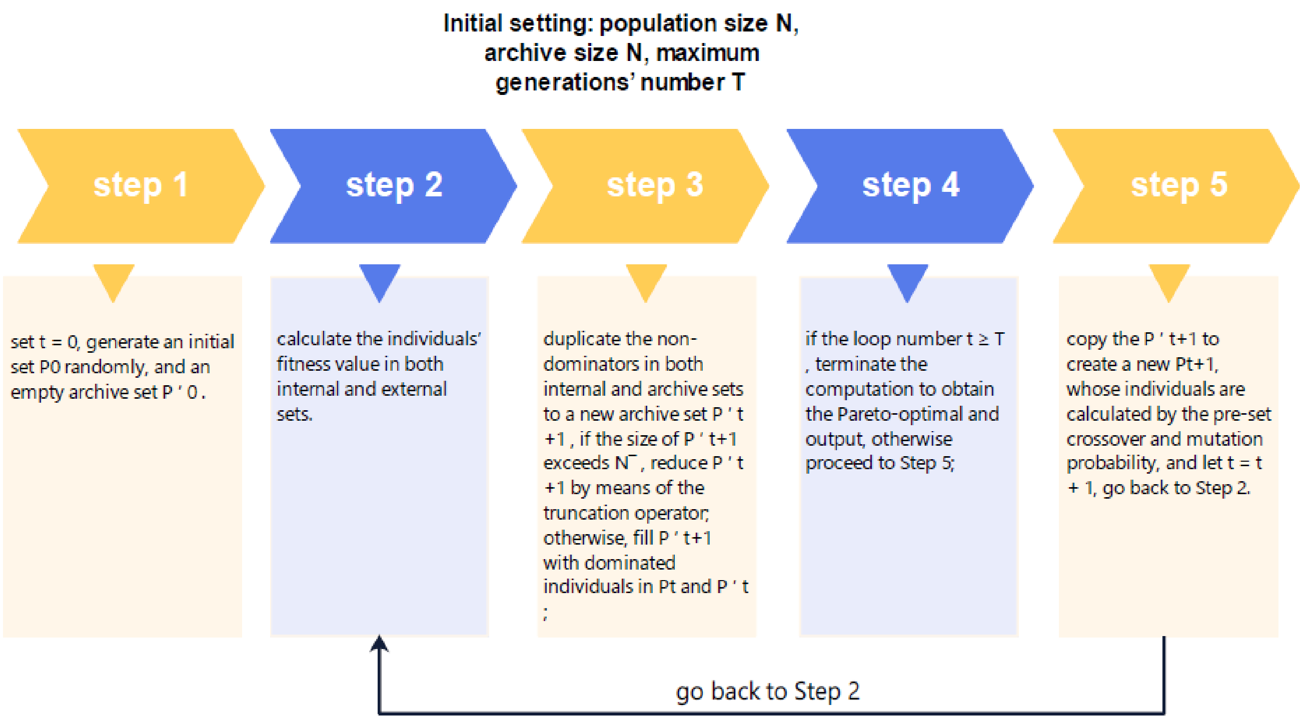

Fig 6. Details steps of Strength Pareto Evolutionary Algorithm (SPEA-II) (Anon n.d.-c)

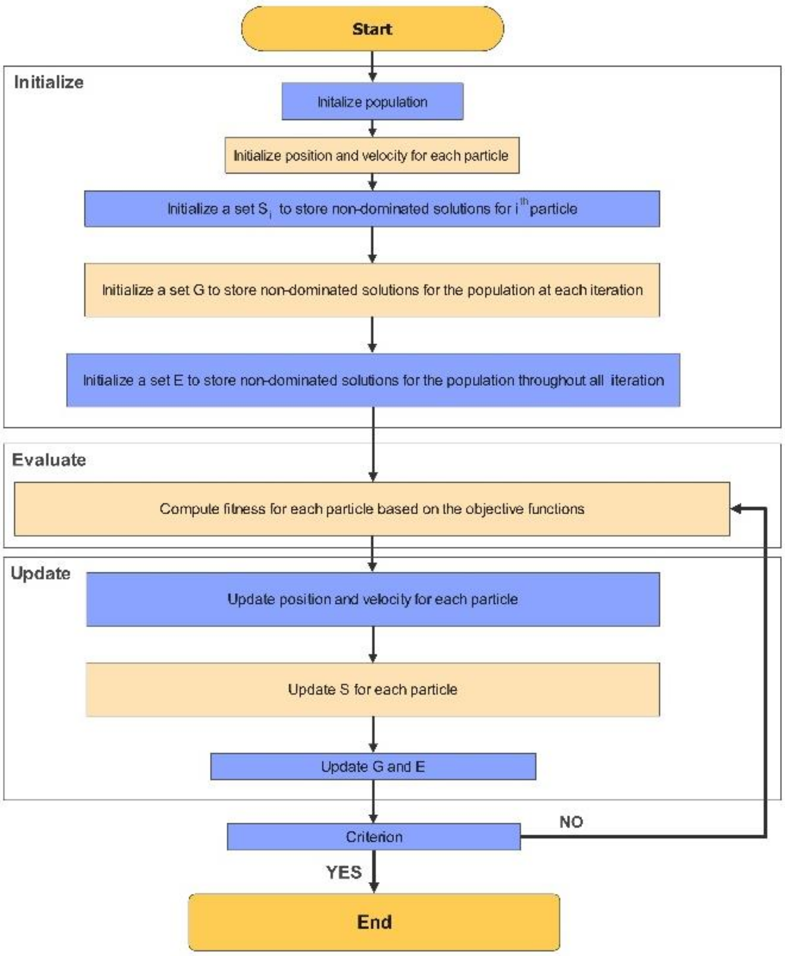

Fig 7. The flow chart of multi-objective particle swarm optimization algorithm. (Kusiak and Xu 2012)

3.4. Multi-Objective Differential Evolution (MODE)

Babu and Jehan (Fan, Wang, and Yan 2017) presented Multi-Objective Differential Evolution (MODE). The algorithm eliminates the dominating answers from the population after every generation. Therefore, the population size decreases with each generation. If the children outnumber the parents, they are integrated into the population. On the test problems, the algorithm performed well, however, there weren't many answers that weren't dominated (Adeyemo and O. Otieno n.d.).

Numerous operators and tactics are put out to address algorithms' drawbacks and enhance their performance with the development of MODE. A multi-objective differential evolution algorithm was created by (Anon n.d.-b). The new principle is utilized to replace the crossover operation in the original DE in order to increase population diversity. In order to increase the diversity of offspring, Qu (Qu and Suganthan 2011) created the diversity-enhanced multi-objective differential evolution algorithm (DE-CMODE), which combines a varied memory bank with current populations. (Bi and Xiao 2011) developed an upgraded MODE with adaptive parameter management approach to speed up convergence and get a better-distributed model (Fan et al. 2022).

A set of Pareto-optimal solutions that represent a trade-off between the various objectives are the output of the MODE algorithm.

3.5. Multi objective Optimization Evolutionary Algorithms (MOEAs)

They are frequently used to resolve MOPs due to their population-based nature, which allows them to deliver the whole set of trade-off solutions in a single run. The three main operators that MOEAs use to try to do this are mating selection, recombination, and environmental selection (Anon n.d.-e).

The algorithm works by creating a population of potential solutions, which is then evolved toward better answers using evolutionary operators including mutation and crossover. The main benefit of MOEA over other optimization methods is its capacity to manage several competing objectives concurrently without forcing the user to explicitly identify trade-offs between them.

This makes it the perfect instrument for maximizing intricate building systems with numerous conflicting goals (Zhang and Li 2007). Building envelope design, HVAC system optimization, and the incorporation of renewable energy sources are just a few applications of the building science for which MOEA has been effectively used. Researchers and engineers can rapidly explore a wide design space and find the best solutions balance multiple objectives by utilizing MOEA (Deb 2001). Many MOEAs have adopted different technical aspects, most of them share a common framework, as shown in Fig.8.

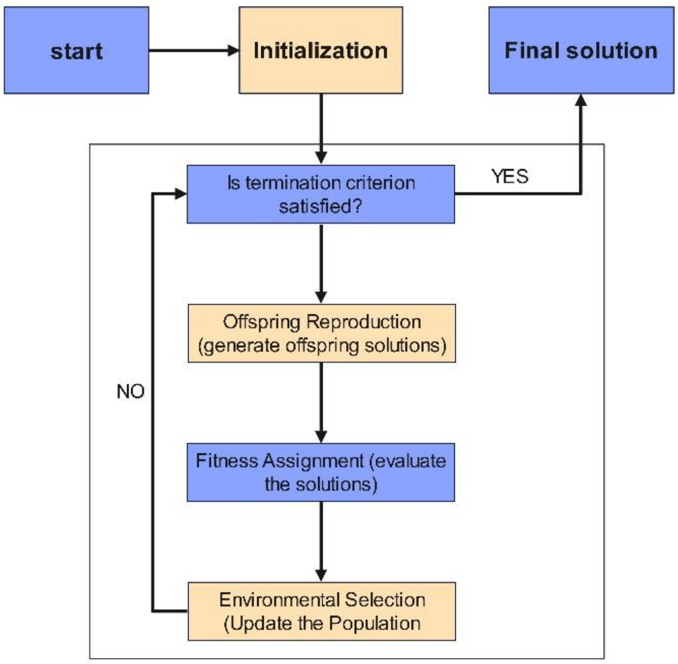

Fig 8. The general frame work of MOEAs(He et al. 2019)

4. CONCLUSION

The majority of real-world problems, such as design, scheduling, modeling, optimization, etc., are inherently multi-objective optimization issues. The optimized goals encompass everything from material or fuel consumption, production, operation and maintenance costs, capital and investment, product yields, product quality indices, and profits to energy efficiency, energy consumption, and pollutant emissions (primarily greenhouse gas emissions) like CO2, SO2, etc.

The trade-off between various competing and cooperative purposes presents one of the major challenges in the solution of multi-objective optimization problems. Finding a solution that renders one goal ideal may cause another goal or goals to suffer unfavorable outcomes. Since the multi-objective issue was first put out, an increasing number of scholars have worked to resolve it using efficient techniques and have come up with workable optimal solutions.

This paper offers a comprehensive analysis of the multi-objective optimization techniques now in use in the field of building energy performance. The review discusses numerous optimization methods, such as genetic algorithms (NSGA-II), evolutionary algorithms, particle swarm intelligence algorithms, and other metaheuristic methods. The review also offers a thorough examination of the advantages/ disadvantages of each technique in various contexts, including thermal performance analysis, ventilation, and daylighting. Finally, the study points out areas in the literature where more research is needed and offers potential directions.

4.1. Non-Dominated Sorting Genetic Algorithm (NSGA-II)

The Non-Dominated Sorting Genetic Algorithm (NSGA-II) method is the most frequently used technique, according to studies. The table below lists some of the most significant studies conducted in this field. The methodology for identifying the publications has been based on the thermal behavior of buildings and the types of algorithms employed.

China and Iran have the most studies in this area, and the trend of adopting this algorithm has significantly increased between 2009 and 2022.

4.2. Others algorithms

Although NSGA has been used much more than other optimization techniques for studying the energy consumption of buildings, researchers are now attempting to replace it with other methods due to its weaknesses. In place of NSGA, researchers have increasingly utilized MODE, which addresses multiple concurrent issues with different algorithms. The output of the MODE algorithm comprises a set of Pareto-optimal solutions that demonstrate a trade-off between various goals.

Table 1. A List of Well-Known Non-Dominated Sorting Genetic Algorithm (Nsga-Ii)

Names	Authors	Algorithms	Method	Keyword
(Wu and Zhang 2022)	Wu and Zhang	(NSGA-II)	1-extract parametric design variables 2-modeling and calculation process of building performance 3-process of MOO and data analysis	Building envelope-Multi-objective optimization Energy consumption-Visual comfort-Thermal comfort
(Sharif and Hammad 2019)	Sharif et al	NSGA-II	Building Envelope, Renovation	optimizing the energy consumption
(Anon n.d.-h)	Echenagucia et al	(NSGA-II)	minimize the energy need for heating coiling and lighting	Multi-objective optimization-Genetic algorithm Early design stage-Building envelope Building energy optimization-Building energy performance
(Gossard, Lartigue, and Thellier 2013)	Gossard et al	genetic algorithm NSGA-II + ANN	using artificial neural networks (ANN) with genetic algorithm NSGA-II to solve the problems	Keywords: Multi-objective optimization envelope Building performance Energy degree Comfort ANN algorithm Genetic
(Adeyemo and Amusan 2022)	Adeyemo and Amusan	genetic algorithm (NSGA-II)		Multi-objective optimization Net zero energy building Non-dominated sorting genetic algorithm (NSGA-II) Hybrid renewable energy system Retired

Names	Authors	Algorithms	Method	Keyword
				electric vehicle battery Lithium iron phosphate battery
(Gou et al. 2018)	Gou et al	ANN NSGA-II	1- defining objective functions 2- defining variables 3-multiobjective optimization by coupling NSGA-II with an ANN	Multi-objective optimization; Artificial neural network; Genetic algorithm; Thermal comfort; Energy demand
(Hosamo et al. 2022)	Hosamo et al	ML algorithms genetic algorithm (NSGA-II)	provides a novel multi-objective optimization strategy for reducing energy consumption in buildings while increasing occupant comfort by using eleven machine learning algorithms and the NSGA II technique	Building information modeling Multi-objective optimization Building energy consumption Thermal comfort linear regression NSGA II
(Gao et al. 2023)	Gao et al	genetic algorithm (NSGA-II)	modeling and multi-optimization workflow using transient system simulation (TRNSYS) and jEPlus + EA + genetic algorithm	Multi-objective optimization Climate change Newly retrofitted office building Energy savings NSGA-II
(García Kerdan, Raslan, and Ruyssevelt 2016)	karden et al.	genetic algorithm (NSGA-II)		Building simulation-Exergy Optimisation-Genetic algorithms Building retrofits-Non-domestic buildings
(Zou et al. 2021)	Zou et al	genetic algorithm (NSGA-II)		Climate change-Artificial neural networks Multi-objective optimization Genetic algorithm Building performance
(Zhai et al. 2019)	Zhai et al	(NSGA-II)	in this paper, a multi-objective optimization method combining Energy Plus and NSGA-II is presented to obtain optimal window design solutions	Multi-objective optimization; window design; NSGA-II; energy consumption; thermal environment; visual performance
(Vukadinović et al. 2021)	Vukadinović et al	genetic algorithm (NSGA-II)	Optimization of a passive solar building with a sunspace was performed using (NSGA-II) through Design Builder software coupled to Energy Plus	Passive solar building-Sunspace-Energy performance Multi-objective optimization-NSGA-II
(Yang et al. 2017)	Der Yang et al	(NSGA-II)		Green building; Multiobjective optimization; Nondominated sorting genetic
(Sayegh et al. 2023)	Sayegh et al	genetic algorithm-II (NSGA-II)		Multi-objective optimization Computational time reduction Typical day selection algorithm Genetic algorithm
(Rosso et al. 2020)	Rosso et al	genetic algorithm (aNSGA-II)		Building energy retrofit-Multi-objective optimization Building performance optimization-Building energy optimization-Genetic algorithm-aNSGA-II-Energy performance-Dynamic simulation EnergyPlus-Mediterranean climate
(Ghaderian and Veysi 2021)	Ghaderian and Veysi	NSGA-II algorithm		Multi-objective optimization-Building energy consumption-Thermal comfort-Response surface design-Regression model-NSGA-II
(Ciardiello et al. 2020)	Ciardiello et al	aNSGA-II algorithm		Building geometry-Shape coefficient-nZEB-BEO Genetic algorithm-Multi-objective optimization

Names	Authors	Algorithms	Method	Keyword
(Fabrizio Ascione et al. 2019)	Ascione et al	genetic algorithm (NSGA-II)		Building design -Energy efficiency Building energy simulation-Building energy optimization Multi-objective genetic algorithm Cost-optimal analysis
(Acar, Kaska, and Tokgoz 2021)	Acar et al	NSGA-II algorithm	In this paper, a Matlab code, which can run NSGA-II genetic algorithm and build an energy analysis program together, was developed. By shortening the optimization period	Multi-objective optimization Building envelope Preliminary design Zero energy buildings Turkey
(F. Ascione et al. 2019)	Ascione et al	NSGA-II algorithm	proposes a multi-objective optimization approach to address the energy design of the building envelope. A (GA) is implemented by means of the coupling between MATLAB® and Energy Plus to minimize energy consumption, energy- cost and discomfort hours (DH)	Building envelope-Building energy optimization Multi-objective genetic algorithm-Cost-optimal analysis-Nearly zero energy buildings Thermal comfort
(Si et al. 2019)	Si et al	NSGA-II algorithm		Building design optimization Artificial neural network Multi-objective optimization algorithms Performance evaluation of algorithms Real-world building design
(Tavakolan et al. 2022)	Tavakolan et al	NSGA-II algorithm under MATLAB	1-defines the building model in energy plus 2-introduces the variables and creates a parametric model 3- the objective functions are discussed and formulated 4-performs a multi-objective optimization using NSGA-II algorithm under MATLAB 5	Building energy retrofit-Multi-objective optimization Parallel computing-Energy efficiency Genetic algorithm Energy pricing policy
(Samarasinghalage et al. 2022)	Samarasinghalage et al.	NSGA-II algorithm		Building-integrated photovoltaics (BIPV) Building envelope design Multi-objective optimization (MOO) Energy Cost
(He and Zhang 2022)	He and Zhang	elite strategy NSGA-II algorithm		Bi-objective optimization-Energy consumption Investment cost-Public building envelope design e-constraint method

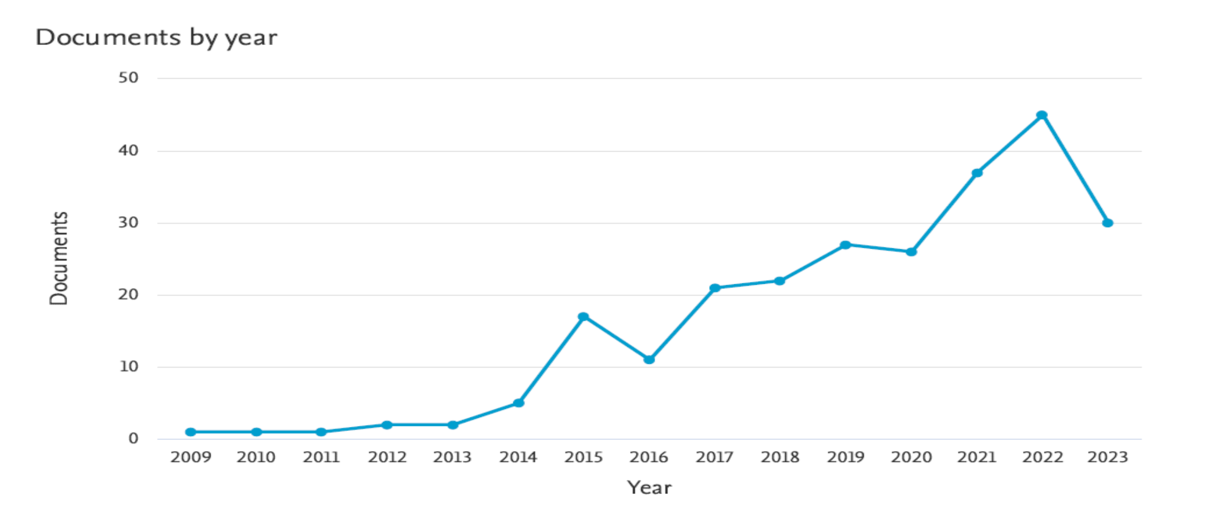

Fig 9. NSGA-II and Building Energy per years based on Scopus scientific database

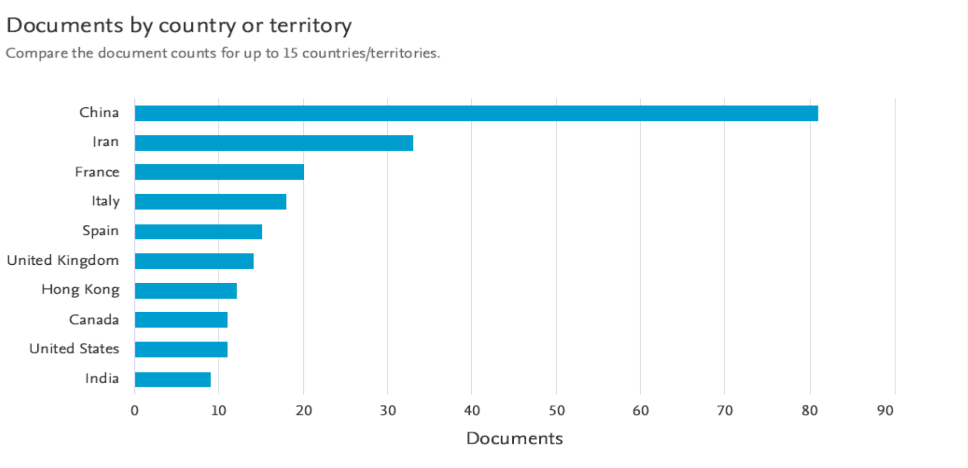

Fig 10. NSGA-II and Building Energy per country based on Scopus scientific database

Table 2. A List of Others Algorithms

Names	Authors	Algorithms	Method	Keyword
(Anon n.d.-g)	Hamdy et al	NSGA-II (pNSGA-II) (MOPSO) (ENSES), (evMOGA), (spMODE-II), (MODA)	compares performance of seven commonly-used multi-objective evolutionary optimization algorithms in solving the design problem of a nearly zero energy building	multi-objective optimization; algorithms; experimentation; building simulation; comparison
(Huang, Fang, and Deng 2020)	Huang et al	genetic algorithm		Distribution network, Electric vehicles, Multi-objective optimization, Coordinated dispatch, Advanced genetic algorithm
(Asadi et al. 2014)	Asadi et al	Genetic Algorithm	using Artificial Neural Network and Gentic algorithm	Building retrofit, Multi-objective optimization, Genetic algorithm, Artificial neural network, Energy efficiency, Thermal comfort
(Kim and Clayton 2020)	Kim et al	SPEA-2 and HypE algorithms.		Parametric behavior map (PBM) Climate-adaptive kinetic facade Multi-objective optimization Building energy Daylighting Dynamic operations schedule
(Fan and Xia 2017)	Fan and Xia	genetic algorithm	multi-objective optimization model for a building envelope retrofitting plan. The aim of this study is to improve the energy efficiency of existing buildings	Building envelope retrofit, multi-objective optimization, rooftop PV system, economic analysis
(Fan and Xia 2015)	Fan and Xia	multi-objective optimization problem was solved by using MATLAB.	ptimal building envelope retrofit plan for existing buildings formulated as a multi-objective optimization problem and solved in MATLAB	Building envelope retrofit; energy efficiency; life-cycle cost.
(Yao et al. 2022)	Yao et al	SPEA-II algorithm	evaluate present situation of rural residences-prototypical models will be established based on the result of investigation-build the performance optimization platform based on energy software carry out multi-objective optimization to obtain the optimal design strategy	Rural residences Prototypical model Transparent building envelope Multi-objective optimization

Names	Authors	Algorithms	Method	Keyword
(Azari et al. 2016)	Azari et al	hybrid genetic algorithm (GA) and artificial neural networks (ANN)		life cycle assessment (LCA), building envelope, optimization, genetic algorithm
(Chegari et al. 2021)	Chegari et al	(NSGA-II), (MOPSO) (MOGA).	comparative analysis to find the best solutions and algorithms such as MOPSO/ NSGA-II/MOGA	Energy efficiency-Passive strategy-Energy performance Thermal comfort-Multi-criteria decision-Artificial neural networks-Surrogate model-Metaheuristic algorithms
(Xu et al. 2021)	Xu et al	NSGA-II and MOPSO algorithm	The application of the NSGA-II and MOPSO algorithm in building envelope optimization is compared.	Building design optimization Meta-model School teaching buildings Multi-objective
(Yong et al. 2020)	Yong et al	BBMOPSO-A algorithm	proposed a multi-objective evolutionary algorithm, BBMOPSO-A, to deal with the optimization problem of building energy performance and compared with traditional particle swarm optimization algorithms	Building energy performance, multi-objective optimization, particle swarm, EnergyPlus
(Zhu, Wang, and Sun 2020)	Zhu et al	SPEA-2 algorithm	1-understanding the present situation of RTBs in north China and benchmark models of the RTB 2-setting up the simulation-based MOO problem by analyzing and defining the variables 3-running the MOO simulation and analyzing the optimum results	Rural tourism buildings-Multi-objective optimization Comprehensive performance-Building shape Window to wall ratio
(Liu and Rodriguez 2021)	Liu and Rodriguez	Adaptive Sparrow Search Optimization Algorithm (ASSOA)		Multi-criteria optimization, renewable energy sources, Adaptive Sparrow Search optimization algorithm, cost-optimum evaluation, building energy behavior, building transient simulation
(Chang, Castro-Lacouture, and Yamagata 2020)	Chang et al	genetic algorithm		Building envelope retrofits-Multi-objective optimization Uncertainties- Internet of things Adaptable decision support
(Zhang et al. 2017)	Zhang et al.	SPEA-2 algorithm	SPEA-2, is implemented to optimize the thermal and daylight performance of school buildings in cold climates of China with the aim to maximize both visual and thermal comfort	School building, energy demand, adaptive thermal comfort, useful daylight illuminance (UDI), multi-objective optimization, China, cold climate

4.3. Evaluation Performance of Multi-objective Algorithms Optimization Methode

The evaluation of meta-heuristic algorithms in solving large-size problems involves assessing the performance of four meta-heuristic algorithms: MOPSO, NSGA-II, SPEA-II, and MOEA/D. This evaluation is conducted using 15 different large-size numerical examples. The assessment criteria include the Number of Pareto Solutions (NPS), Mean Ideal Distance (MID), The Spread of Non-dominance Solutions (SNS), and CPU Time.

(A) Number of Pareto Solutions (NPS): This criterion calculates the number of non-dominated solutions that are obtained each time by applying the algorithm. According to this criterion, the greater number of non-dominated solutions shows that the algorithm works better.

(B) Mean Ideal Distance (MID): This shows the distance between Pareto points and the ideal point for each algorithm. The lower value of this index indicates the superiority of the algorithm.

(C) The Spread of Non-dominance Solutions (SNS): This criterion calculates the dispersion between the set of non-dominated solutions that are obtained by the algorithm, and is calculated by Eq. The dispersion of the solution is higher and more desirable for the greater SNS values.

(D) CPU Time: The computational time of the algorithm is one of the most crucial indicators of the efficiency of each meta-heuristic algorithm.

The result obtained through the implication of described meta-heuristic algorithms was statistically analyzed in terms of NPS, MID, SNS, and CPU time at a 95% confidence interval. This statistical analysis demonstrated the MOEA/D algorithm as the best method among applied meta-heuristic algorithms in terms of NPS and SNS (p-value<0.05). However, the SPEA-II algorithm performed better in terms of MID and CPU Time e (p-value<0.05) (!!! INVALID CITATION !!!) [1]

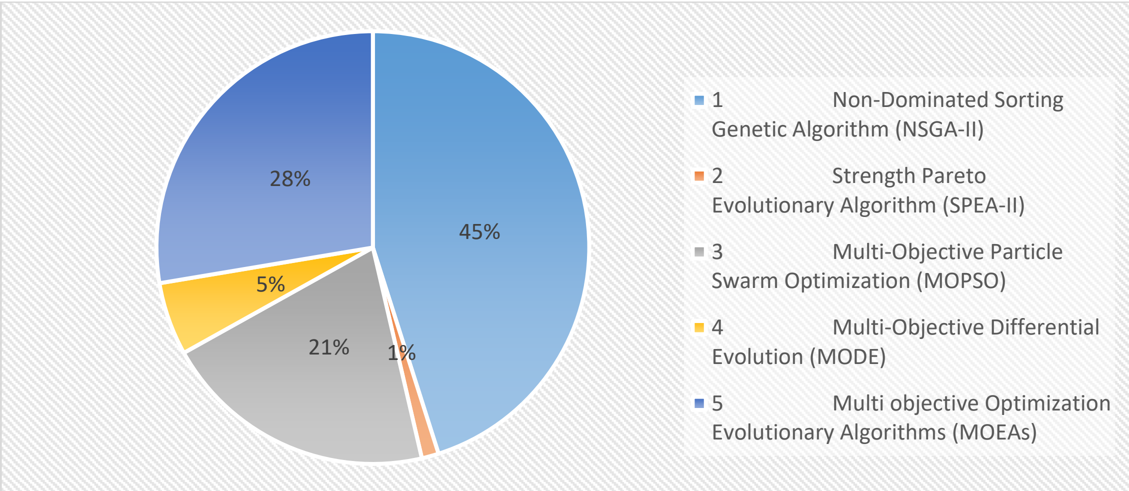

Fig 11. The Frequency use of multi objective methods in researches

Table 3. meta-heuristic methods to evaluate model performance for large size problems

meta-heuristic methods to evaluate model performance for large size problems															
MOEA/D				**SPEA-II**				**NSGA-II**				**MOPSO**			
Time (s)	**SNS**	**MID**	**NPS**	**Time (s)**	**SNS**	**MID**	**NPS**	**Time (s)**	**SNS**	**MID**	**NPS**	**Time(s)**	**SNS**	**MID**	**NPS**
356.11	1.86	0.84	32	162.57	0.85	0.67	17	198.32	0.91	0.64	17	140.13	0.24	0.57	7
244.52	1.90	0.92	32	163.91	1.05	0.67	19	210.87	0.93	0.57	14	191.35	0.33	0.81	5
191.03	2.47	0.74	29	136.53	0.76	0.73	11	181.85	0.82	0.57	7	472.21	1.85	0.65	14
142.13	1.79	0.81	33	95.62	0.90	0.54	18	115.35	1.06	0.65	16	80.64	0.66	0.79	9
197.22	1.09	0.89	27	136.50	0.96	0.65	16	186.41	0.70	0.68	7	150.75	0.28	1.10	8
601.90	1.71	0.80	27	411.84	0.69	0.65	7	508.04	0.67	0.67	11	856.31	0.09	0.96	4
296.94	2.02	0.53	26	191.11	0.77	0.61	16	278.22	0.68	0.67	14	876.31	0.27	0.91	8
112.93	0.82	1.18	23	112.07	0.85	0.64	16	99.91	0.77	0.57	16	786.31	0.01	1.00	7
130.50	1.84	0.71	24	91.27	0.82	0.65	17	111.57	0.96	0.54	21	658.31	0.65	0.80	4
358.37	1.78	0.68	28	151.52	0.87	0.66	18	235.91	0.69	0.70	14	440.26	0.33	0.96	9
119.55	2.03	0.92	29	69.94	0.85	0.64	14	84.81	0.90	0.62	18	580.12	0.62	0.76	9
99.10	2.09	0.87	34	71.81	0.76	0.68	15	122.25	0.82	0.63	13	161.91	0.77	0.74	10
62.36	2.18	0.82	28	69.81	1.08	0.66	19	68.87	0.30	1.06	13	152.87	0.49	0.82	9
97.26	1.10	0.75	27	66.39	0.96	0.57	12	97.68	0.30	1.08	16	147.90	0.49	0.80	5
227.42	1.88	0.85	31	161.60	0.99	0.52	13	192.36	0.76	0.63	9	362.83	0.74	0.86	7
215.82	**1.77**	**0.82**	**28.667**	**139.50**	**0.88**	**0.64**	**15.2**	**179.49**	**0.75**	**0.69**	**13.733**	**478.24**	**0.52**	**0.84**	**7.667**

small, medium, and large sizes are determined based on the model index. If the index of the problem is less than 50 or 60, the problem is considered as small size, for the indexes greater than 80 or 90, the problem is considered as a large size problem, and indexes between 60-80 demonstrate the medium size problem. A holistic view regarding the importance of selecting an appropriate solution methodology based on the problem dimension to ensure obtaining the optimum and accurate solution within the reasonable processing time.

Table 4. Appropriate solution methodologies based on optimum and accurate solution within reasonable processing time

Major optimization methods	Property	Parameters	Low	Medium	High	Ideal
Non-Dominated Sorting Genetic Algorithm (NSGA-II	✓ elitist principle ✓ diversity preserving mechanism ✓ non-dominated solutions ✓ comparison purposes ✓ solving multi-objective problems	Max iteration	60	80	100	100
		Population Size	50	70	90	90
		Crossover Percentage	0.5	0.7	0.9	0.5
		Mutation Percentage	0.2	0.4	0.6	0.2
		Mutation Rate	0.01	0.02	0.03	0.01
Strength Pareto Evolutionary Algorithm (SPEA-II)	✓ powerful multi-objective algorithms ✓ comparison purposes ✓ using external archive to keep the non-dominated solutions during the searching process ✓ calculating the fitness and strength values ✓ using k-nearest neighbor strategy to calculate the density of individuals	Max iteration	60	80	100	100
		Population Size	50	70	90	90
		Archive Size	80	90	100	90
		Crossover Percentage	0.5	0.7	0.9	0.9
		Mutation Percentage	0.1	0.3	0.5	0.5
Multi-Objective Particle Swarm Optimization (MOPSO)	✓ multi-objective model ✓ stochastic, population-based evolutionary algorithm	Max iteration	60	80	100	80
		Population Size	50	70	90	90
		Repository Size	80	90	100	100
		Inertia Weight	0.1	0.3	0.4	0.1
		Number of Grids per Dimension	3	4	5	3
		Inflation Rate	0.1	0.3	0.5	0.1
		Leader Selection Pressure	0.5	1	2	0.5
		Deletion Selection Pressure	0.5	1	2	2
		Inertia Weight Damping Rate	0.75	0.85	0.95	0.75
		Personal Learning Coefficient	0.5	1	2	2
		Global Learning Coefficient	0.5	1	2	2
		Mutation Rate	0.1	0.3	0.5	0.1
Multi-Objective Differential Evolution (MODE)	✓ multicriteria and multiconstrained algorithms ✓ multi-objective optimization ✓ non-dominated solutions ✓ non-dominated sorting, ranking, and crowding distance assignment					

Major optimization methods	Property	Parameters	Low	Medium	High	Ideal
Multi objective Optimization Evolutionary Algorithms (MOEAs)	✓ large number of objectives solving complex problems ✓ well-converged and well distributed set of solutions in a very small computational time ✓ synergistic manner ✓ Pareto envelope-based selection algorithm or PESA ✓ non-dominated solutions ✓ less-crowded hyper-box selection and the offspring-acceptance operators ✓ comparison purposes	Max iteration	60	80	100	80
		Population Size	50	70	90	90
		Archive Size	80	90	100	80
		Number of Neighbors	10	20	30	10
		Crossover Percentage	0.1	0.3	0.5	0.1

4. DISCUSSION

Future suggestions that will be considered for this paper encompass various avenues of research and development:

I) Incorporating fuzzy decision methods and robust optimization methods to effectively address uncertainty in the research.

II) Implementing the proposed model in a real-world case study to evaluate its practical flexibility and applicability.

This is an essential step that can lead to the calibration of the proposed model.

III) Expanding the scope of objective functions by considering additional environmental criteria and social assessment indicators.

IV) Extending the analysis considering more effective factors to assess the reliability and quality indices of the final results.

V) considering the use of the AI-based model with a higher level of autonomy in analysis.

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