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Systematic Review

An Extensive Study for a Wide Utilization of Green Architecture Parameters in Built Environment Based on Genetic Schemes

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Abstract: Recently, green structures turned into a huge path to an economic future. Green building outlines include finding the harmony between agreeable home living and a maintainable environment. Furthermore, the usage of modern technologies is seen as part of greener construction changes to make the urban environment more viable. This paper introduces an exhaustive state-of-art review and current practices to look for the ideal green arrangement's models, procedures, and parameters utilizing the genetic algorithms innovations to help for settling on the most ideal choice from various options. The integrated Genetic Algorithm (GA) along with the Nondominated Sorting Genetic Algorithm strategy GA-NSGA-II is considered to be more accurate for predicting a viable future. The above methodology is widely relevant for its humility, ease of execution, and enormous durability. Besides other approaches, the GA was incorporated as well as the Neural Network (NN), Simulated Annealing (SA), Fuzzy Set theory, decision-making multicriteria, and multi-objective programming. The most fashionable methods are moderately the embedded GA-NSGA-II approaches. This paper gives an outline of the capability of GA-based MOO in supporting the advancement of methodologies of the techniques and parameters to find the best solution for the building decision-making cycle. The GA combined schemes can fulfill all the requirements for finding the optimality in the case of multi-objective problem-solving.

Keywords: genetic algorithms; optimization; green architecture; technologies; strategies techniques; models

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1. Introduction

Building structures that offer agreeable, flexible, vitality efficient, and living environment at a lower cost are desired by building proprietors and occupiers. To accomplish this, enhancing the building performance to fulfill an assortment of human needs and natural sustainability is needed [1]. Green strategies are a part of the outline procedure in engineering, scene design, and urban planning [2]. The ecological compositional model is regularly listed as follows: finding achievable solutions for an arrangement of interrelated variables, for example, renewable energies [3], eco-designs [4], solar energy [5–7], lighting [8], compressed shopper waste blocks [9], waste disposal [10], air-conditioning facilities [11], ventilation designs [12,13], shading designs [14], heating systems [15,16], green roofs [17], building envelopes [18], wall insulation for buildings, and double-skin facades [19–21]. These not only fulfill the preconditions of the outline, but also maximize the quality of the plan, as outlined preferences further satisfy both stylish and convenience requirements. The potential utilization of data, innovations, and Artificial Intelligence (AI) calculations in preference of enabling decision-making networks are well known in urban planning. With the approach of fast web advances, enhanced graphical automation, and complex AI systems, spatial appraisal and optimization are currently viewed as noteworthy regions of research [22]. Likewise, in looking at a vast state-space, multi-model, or n-dimensional surface as the analysis of the building portrayed here, the GA may offer noteworthy that is portrayed here, the GA may provide significant benefits over the most growing set of optimization procedures [23,24]. This paper is a profitable survey of different GA advances that are utilized as a part of green building enhancement and evaluation, inside the extent of environment effect appraisal, and decision support. The GA is merged into this inquiry because it is different than some regular AI since it is better, whereas GAs are stochastic optimization techniques that can solve the multi-objective optimization problem. Also, it assesses the past research in the zone of urban planning and recharging as far as data representation and choice support tools as well as strategies and models for urban subsystems. The discussion makes determinations over the present best in class using the various GA and the developmental calculations methods in the natural virtual simulation and recognize pertinent learning knowledge. At last, the paper presents a few reviews with a view to the ultimate goal of developing an optimization solution to assess different socioeconomic deprivation factors. In doing so, the same approach of [25] is adopted in this paper to extend and update the review of computational optimization methods, particularly those based on GA.

The paper is categorized according to the following sections: Section 2 clarifies the genetic algorithm as an optimum search-technique with the GA issues and approaches that were combined with green architectural optimization techniques. In Section 3, the results and discussion, we investigate the issues that can be tended to by all the work alongside the outline of the survey. Finally, the article finishes with Section 4, concluding that the genetic algorithm (GA) is the most common approach in the construction of performance analysis. The GA algorithm calculation impersonates the procedure of the advancement of populaces by selecting just fit individuals for propagation. Thusly, the GA is an ideal pursuit procedure despite the ideas of daily decision-making and the most suitable survival. A genetic algorithm uses three main hereditary administrators: selection, crossover, and mutation [26]. Amid each generation in the propagation procedure, the people in the present generation are assessed by their fitness ability, which is a measure of how well the person handles the situation. By then, every individual met in the extent to its fitness: the higher the wellness, the higher its opportunity to take part in mating (hybrid), and to create an offspring, a limited percentage of infant posterity witness the change mutation behavior [27]. After numerous generations, people who have the best hereditary qualities survive, the people that rise out of this "survival of the fittest" procedure is what speaks the perfect solution for the issue determined by the wellness capacity and the limitations [28]. A GA meets expectations by specific reproducing of a populace of "people" could of these be a possible solution to the query [29]. The structure of the standard GA is shown in Figure 1.

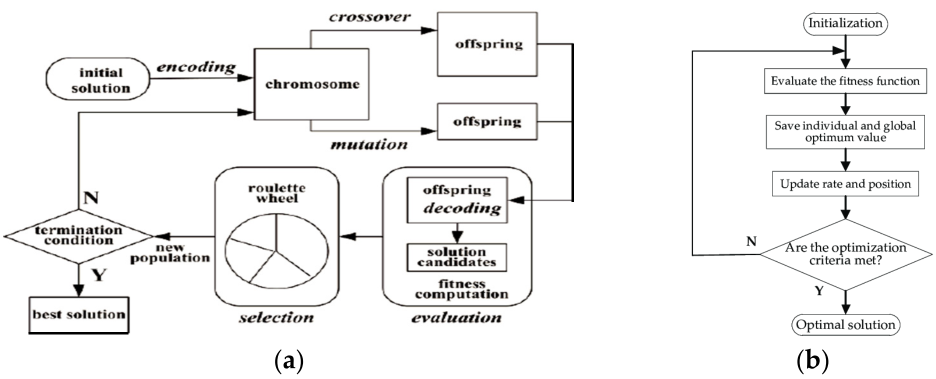


Figure 1. Standard Genetic Algorithm, (**a**) GA Structure; (**b**) GA Algorithm.

Regarding Figure 1, in every generation, individuals are chosen for propagation as shown by the results of the wellness capability. Determination gives a higher shot of survival to better individuals. Consequently, genetic operations are connected to frame new and conceivably better offspring. The calculation is ended either after a specific number of generations or when the solution was found in the case of one global minimum, or we utilize other AI techniques to be combined with the GA to find the optimal solution [30,31]. Computer simulations and numerous software applications for the building design process are presented as an example, such as Ecotect, Energyplus, DOE-2, and TRNSYS [32]. PC simulation is advantageously utilized and was well designed; regardless, it has a few setbacks. Hence, it cannot satisfactorily meet the necessity of the planners or proprietors in the reasonable outline organize. For instance, most of the building simulation tools were at first produced for Heating, Ventilation, and Air Conditioning (HVAC) engineers.

Gaps: Several scholars introduced multi-objective GA schemes that were implemented in the construction sector. They considered the particular priorities for the design of buildings to make the building optimization design easy and more feasible [33–36]. But they did not fulfill all the required parameters to get the most optimal solution for future GA problems.

Motivations: Multitarget improvement formed into a massive research field where significant works incorporate many kinds of research that attempted to help designers to create powerful outlines. The formulation for all the GA parameters helped the users and designers to mitigate all their problem in any case.

2. GA Combination Approaches

A good review in research should include an underlying quest for pertinent works that utilize the web of science, e.g., Elsevier, Springer, Scopus, Library Genesis scientific papers (LibGen), Egyptian Universities Library (EUL), and Egyptian Knowledge Bank (EKB). The research uses the best idioms that formulate the review as some of the research words in the building field like architecture, green, energy, building, optimization, and sustainability. Advanced searches are performed in the journal papers and proceedings. The articles are referred to by the research found were likewise checked for pertinence. Gathering papers from proceedings are incorporated except if comparative journals diary papers exist.

The inquiry is subject to all ranges of reasonable building plans (e.g., thermal comfort, energy consumption resulting in greenhouse gas, and water utilization). Also, this research focusses on technologies used in buildings, where there is noteworthy data on the outline of numerous frameworks like aerating and cooling frameworks, a critical utilization of computational streamlining, and that utilize the term enhancement where it performs just mathematical or manual procedures. A brief overview of the different computational development techniques and their mixes are given, including regular calculations.

Chiranjib et al. [37] conducted surveying for the multiple assessment and selection approaches to energy management from 1957 to 2017 as classification literature of the different articles. They researched the comprehensive sustainable development green energy planning to discover the most convenient energy management approach using GA to realize which methods were implemented in the region, assessing sustainable development requirements in that area. This research helps scientists and decision-makers to apply the processes. It was discovered from the study that many individuals, integrated, and other methods were suggested to solve the issue of energy planning and scheduling. They indicated that there are numerous integrated methods for evaluating and selecting sustainable green energy, and 89.32% of the specific methods were slightly more appealing than the 7.28% of integrated approaches.

The most popular individual method is mathematical programming by using various algorithms. Then, it is followed by the fuzzy methods, physical hybrid energy management system, Analytic Network Process (ANP), ZigBee technology, Analytic hierarchy process (AHP), Data Envelopment Analysis (DEA), Artificial neural network (ANN), GA, Supervisory Control and Data Acquisition SCADA, game theory method, and other techniques [37].

Here, we survey all the best techniques that are valuable for green building technology in case of decision-making and to find the high-performance parameters for green structure. The techniques are based on the GA and its combinations to get the best solution for green building optimization systems.

2.1. GA Approach

Wang S. et al. [38] and Prendes et al. [39] demonstrated that GA measurement is a beneficial method in the quest for optimal settings to reduce the total cost of online ventilation systems regulation. TRNSYS is utilized as the stage for the dynamic emulation of aeration and cooling systems that include design areas and monitoring systems. This work is based upon a past study [40], which included three texture properties as factors. The building's texture elements are the extent of the HVAC framework. They argued the GA could locate a practical arrangement, and it showed an exponential meeting on an answer. Caldas L. et al. [41] introduced a generative tool to improve the design components of buildings and their natural performances. They use GA as a search tool, a thermal and lighting program that utilizes a definite thermal examination program DOE2.1E, and an AutoLisp routine to represent results. The strategy proposed was initially approved in connection to a hand-worked case for the optimal solution to be computed manually. Wright et al. [42] led a multicriteria improvement of the HVAC framework outline and control utilizing a GA. The paper investigated a multi-standard GA search algorithm in the recognizable proof of the ideal result trademark between the energy cost of buildings and the tenant thermal discomfort. The results are exhibited for the result qualities between energy cost and zone thermal comfort for three plan days and three building weights. The approach research showed that the GA should find the best outcome trademark between the day-to-day energy cost and thermal zone comfort. A neural system was additionally used to measured framework performance information [43], and it then reduced chiller running expenses with the incorporation of a GA. A populace-based improvement algorithm (GA) is coupled to a dynamic thermal model with recognizing expansive quantities of different extraordinary low-energy designs [44]. The oddity of this work was the mix of a GA with individual decisions to create an optimal minimization of energy consumption in buildings. Thus, a GA optimization methodology is utilized to minimize the life-cycle ecological effects on buildings [45] in case of considering natural efficiency in the construction of buildings. The life-cycle natural effects are assessed as far as extended combined energy utilization. The ideal solution is discovered utilizing organized GA. In a comparative study, an adaptive network-based fuzzy inference system (ANFIS) scheme is utilized to model conduit and pipe organization to acquire optimal setpoints because of restricted sensor data [46]. The findings revealed that the GA technique ultimately increased system efficiency. Wang et al. [47] revealed a multitarget GA enhancement model that can help the architects in green building outline where the approach's viability is shown for identifying the effectiveness of the solutions from various Pareto solutions. Wright et al. [48] examined the vigor of the GA search strategy in tackling an unconstrained building optimization issue when the amount of construction models used for the upgrade is limited. The GA strategies may be assigned to streamlining agents dependent on probabilistic populations [49]. The usage of the GA scheme with aging to synthesize HVAC systems resulted in a modern design approach having lower energy use than the best of ordinary framework designs. Wang et al. [50] exhibited an object-oriented framework that locates numerous specific qualities of green building design advancement issues, for example, various leveled factors and the coupling with simulation programs. The structure actualized GAs to comprehend unconstrained and compelled single and multitarget optimization issues. The use of this approach is illustrated by a theoretical analysis to explore the comparison of relationships between life-cycle expense and life-cycle ecological effects on green building design. Tanaka et al. [51] detailed the Combined Heat and Power (CHP) framework optimization issue and applied a GA technique with two organize improvement systems (combinatorial and operation advancement). The numerical investigations revealed that the methodology suggested is essential for the optimal construction of CHP frameworks. Verbeeck et al. [52] established a regional plan to automate low-energy homes in a wide measure, considering energy utilization, ecological effect, and money-related expenses throughout the systemic life-cycle of the structure. They utilized a multitarget optimization method to handle this issue by consolidating genetic algorithms and the Pareto idea. The outcomes demonstrated that the GA algorithm is extremely productive if there should be an occurrence of multitarget advancement frameworks. Torres et al. [53] decided the applicability of the GA for the optimization of daylighting frameworks, and preconditions for lighting tests use a few parameters to check the daylight efficiency. The objective of the optimization was to expand energy savings by reducing visual discomfort while retaining massive infiltration of sunlight. The GA demonstrated the reasonability of the technique that connects to daylighting frameworks, even with the generally complex reproduction strategies. Znouda et al. [54] introduced an enhancement algorithm that couples pseudo-arbitrary advancement systems based on the GA with a disentangled instrument for building thermal assessment to reach the end goal of minimizing the energy utilization of Mediterranean structures. The GA represented a fundamental and exceptionally productive approach for addressing non-direct combinatorial enhancement problems, and it can discover great solutions without investigating the entire space of research. Caldas [55] created diverse uses of GENE_ARCH, and advancement-based generative outline frameworks went for helping designers to accomplish energy-efficient and practical building solutions. The framework applies an objective situated plan, joining a GA as the search tool, creating energy modeling technology for DOE2.1E as an assessment tool. The GA functions as a regular GA or as a Pareto GA for checking and advancing multicriteria. Wright et al. [56] built up a model-based advancement technique to combine novel heating, ventilating, and cooling framework setups. The advancement issue considered three sub-enhancement issues; the decision of a part set, the outline of the topological associations between the segments, and the plan of a framework working procedure. Also, a multi-objective GA scheme was utilized to build up the ideal outline strategy for the energy system of single working for the initial step going for building up an ideal design technique for disseminated energy framework [57]. The outcomes demonstrated that GA could manage nonlinear optimization issues. In the study [58], an approach in which a building façade is divided into separate cells is depicted; each cell possesses one from two possible states, a strong wall or a window. A GA seeking technique was utilized to optimize the condition of every cell, and the number or angle proportion of the windows being compelled were attractive. The GA approach brought about outline solutions with intriguing creative compositional structures to minimize the building energy utilized [59]. The improvement comes in conjunction with a Building America Benchmark, which found that the rectangle and the trapezoid shapes were optimal consistently. Congradac et al. [60] exhibited the enhancement of chillers working utilizing counterfeit neural systems and GA. The consequences of the utilization of human-made brainpower and GA techniques in the advancement of chiller operation are checked through an office building model made in the recreation programming EnergyPlus and through a progression of investigations on a genuine office building. Sahu et al. [61] proposed a strategy by consolidating the building's thermal model and an enhancement procedure (GA) to permit energy effective plan for aerated and cooled working in a tropical atmosphere. The GA is a reasonable improvement tool for the outline due to its ability to tackle various forms of building plans considered all the time and its commitment to the optimal solutions worldwide. Huang et al. [62] introduced a strategy for an ideal solid outline of indoor humidity with moisture buffering materials. The outline framework was produced utilizing GA and transient moisture modeling for indoor climate. The Pareto-ideal solution sets were breaking down, and the technique had proved helpful in raising indoor humidity. Stanescu et al. [63] examined an HVAC framework outline enhancement utilizing a definite GA simulation technique. This strategy enhanced the HVAC application setup to eliminate the usage of resources simulated in DOE-2 programming. The elements of a GA created to take care of simulation-based advancement issues for the ideal design of building parameters (heat, construction) are described in the study [64]. The simulation method IDA-ICE and the enhancement method GenOpt were used to discover the ideal estimates of the house envelope preference factors and the HVAC structure. Certifiable enhancement issues in the simulation building performance are completed to check the GA's performance. Chantrelle et al. [65] displayed a multicriteria tool to improve the redesign activities centered on the building of envelopes, heating and cooling pressures, and management techniques. The optimization was performed utilizing a GA, with the simulation of TRNSYS and COMIS. An altered multitarget advancement approach in light of GA [66] is proposed with IDA ICE. The blend should minimize the carbon dioxide comparable outflows, the investment cost for a building, and its HVAC framework. Warming/cooling energy source, warm recovery sort, and six building envelope parameters are considered. The simulation-based development methods showed an immense ability for multitarget resolution of design problems. Evins et al. [67] upgraded the cost and energy utilization of a measured building unit for various atmosphere types. The destinations were carbon emanations and development costs, and the enhancement was performed utilizing a multitarget GA. The considerations guaranteed the properties of sunshine and shape and warming and cooling systems and sustainability, while the imperatives reflected the rooftop area and comfort. The results showed that the GA gives a profitable guide to the basic leadership preparation in both general and particular terms. Hamdy et al. [68] presented a strategy for investigating the characterized solution space by a proficient multitarget GA. The solution is used to discover financially energy productive mixes of the design variations, which affect the thermal execution of the house as the building envelope and the warmth recovery unit. The multi-optimization strategy can minimize study effort and enable a very efficient and clear review. Jin et al. [69] presented a recently developed entire life esteem-based façade outline and improvement tool GA on a genuine façade redesign extend. They represented the way toward distinguishing the advanced façade. The significant consequence of the study was the best façade advancement solutions that enhance the social, natural, and monetary estimation of the working at a reasonable capital financial cost. Evins et al. [70] estimated a multitarget streamlining given the GA for the highly important considerations of a private building in terms of the accuracy of UK building controls. The targets were cost and carbon emanations, where the carbon discharges were figured utilizing the Standard Assessment Procedure (SAP). Ahmadi and Dincer [71] illustrated an evolutionary genetic algorithm for the cogeneration scheme producing electricity for combined heat and power plants. The findings indicated that the specification parameter values increase with the increase in net energy output as expected for a given unit fuel price. Shaikh et al. [72] developed a multiagent control scheme under stochastic optimization using a genetic algorithm for building power management. The software was used to represent effective energy management and customer comfort. The advanced control system significantly improved energy consumption and interior environment comfort. Tong [73] indicated that the GA-based distribution index (IOD) technique can generate a building scheme that offered significant flexibility in the location of the dwellings. The model's findings are considered a beneficial reference in the case of planning green space buildings. Yang et al. [74] incorporated simulation-based energy consumption optimizing for complex construction based on stochastic algorithms. They submitted a web-based parallel GA optimization for a test structure in Spain using distributed computing environment facilities to reduce the running time of complex energy optimization systems. The findings obtained for the test construction demonstrated a substantial reduction in computation time while still achieving acceptable optimal outcomes. Rafiq & Russell [75] incorporated an Interactive and Visual Genetic Clustering Algorithm (IVCGA) into the Building Information Modeling (BIM) environment to improve design data and enable approaches as information model building. The suggested structure helps architects, structural engineers, and building physicists to determine multidisciplinary construction specifications allowing a wide variety of concept models. They executed a case study to locate the efficiency of the multi-objective search engine to optimize the model. Wright et al. [42] used a multi-objective genetic algorithm to determine trade-offs between energy costs and Thermal Comfort (TC) in designing a single zone HVAC system. Results of the cost-off features are provided for three design days and three building weights between energy cost and heat area convenience. The results indicated that multicriteria of genetic algorithm search techniques offer excellent potential to identify the pay-off between building heat design components and the design process of the construction. Hamdy et al. [66] incorporated an updated GA-based optimization technique by IDA-ICE (Building performance Simulation Program). The scheme is used to minimize (CO_2) emissions and investment costs for a two-story building with its HVAC units. Their results indicated 32% less CO_2 emissions and 26% reduced investment price compared to the original design. Also, the scheme minimizes much overheating in the summer and extra shading option costs. Yoon, E.J., [76] researched a timing model to assess the position and form of greens based on their various effects (e.g., cooling and connectivity improvement) and uses metaheuristic optimization algorithms to calculate execution costs. They acquired 30 Pareto-optimal plans for hypothetical neighborhood landscapes. Their results demonstrated a synergistic connection between the cooling and the improving connectivity of buildings, as well as a trade-off between the greenery effects and the cost of execution. Zahra et al. [77] used a multi-objective optimization GA with the SPEA2 sustainability approach to optimize an office building facade based on the cooling load, the heating load, and the natural light given to the building. The results indicated that without considering the effect of openings, the optimization results in a decreased thermal load and an increase in internal space.

2.2. GA, Monte-Carlo

Garshasbi et al. [78] designed a novel hybrid Genetic Algorithm and Monte Carlo simulation strategy to predict instantaneous and cumulative net renewable energy balance and the hourly quantity of energy grid receives and supplies. The remodeled model was able to adjust and modify the energy use habits in buildings by the legislation objectives and well-designed control systems.

2.3. GA-NSGA-II

Yang et al. [74] displayed a high-through measurement system expressed electronically in parallel NSGA-II to calculate the time of simulation-based building energy streamlining issues. The improvement structure was used as a portion of an EU FP7 extension—SportE2 (Sports Facilities Energy Efficiency) to lead broad-scale structures energy utilization improvements for a testing building, KUBIK in Spain. The results demonstrated a significant calculation time reasoning while still obtaining adequate ideal results.

Inyim P. et al. [79] presented building plans utilizing life cycle appraisal and vitality simulation. They used SimulEICon with NSGA-II as a tool to improve the building plans to enhance the ability of vitality. They used a Monte Carlo simulation to address data instability and availability, and EnergyPlus as a part of a demand to figure out the arrangement of energy use.

Wei Yu et al. [32] presented a multitarget optimization model that helps planners in green building outlines. This approach employed to consider a course of action perfect solutions for building outline advancement and utilizations an enhanced multi-objective GA (NSGA-II) as a theoretical reason for building plan multitarget enhancement shows. The findings for the inquiry revealed changes for energy execution and unimportant change to conduct indoor thermal comfort.

Germán et al. [80] provided a procedure to solve one of the big problems with the use of comprehensive energy construction models in Simulation-based Model Predictive Control (MPC) procedures. Three primary novel methods are created: a reduction of the genetic algorithm search room (NSGA-II) due to the use of the free oscillation curve; a decrease in convergence moment based on a two-stage method; and finally, a methodology for evaluating the algorithm's spatial consistency and the precision of the answer obtained in a combined manner.

Yu-Hao et al. [81] studied the air conditioning system and the building envelope configurations by recommending a decision model (MOBELM) multi-objective optimal building envelope. The first refers to the lowest possible construction cost, while the second is concerned with minimizing CO_2 emissions during the manufacturing and application of envelope materials. The results indicated that the optimized design saves lower annual energy consumption by 58.3% of the CO_2 emissions, while increasing 5.3% of the construction cost.

2.4. GA-NSGA-II, Fuzzy, AHP

Yifang et al. [82] simulated an indoor comfort model based on heat weights and air quality using the multi-objective optimization methodology NSGA-II. The findings showed that indoor comfort and energy consumption are decreased based on the simulator on the elevated occupancy density rooms in summer for government buildings. The study objects are university offices, classrooms, and reading rooms in Xi'an, China. The important variables are air quality, thermal environment, weights, indoor relative humidity, indoor air temperature, and the concentration of indoor CO_2.

2.5. GA-PA-NSGA-II

Salminen et al. [83] led a multitarget Pareto Archive PA-NSGA-II streamlining of cost against change over the LEED gauge. They combined energy modeling and improved multicriteria for the building that was LEED-affirmed. The simulation utilized was IDA ICE, which is a product acknowledged for LEED energy recreation. Many factors were settled for the advancement to diminish incredibly energy utilization.

2.6. GA-NSGA-II, ANNs, MFNN, MOPSO, MOGA

Badr Chegari et al. [84] created a novel multi-objective optimization approach based on the Building Performance Optimization (BPO) strategy, which combines (ANNs), (MFNN), (NSGA-II), (MOPSO), and (MOGA) to reduce calculation time. The goal was to increase residential buildings' internal thermal comfort and energy consumption, using the TRNSYS software in a Moroccan building. The findings demonstrate that this technique leads to a variety of recommended building envelope design options. The heating and cooling requirements were decreased to 74.52%, and the internal thermal comfort improved by 4.32%.

2.7. GA-NSGA-II, ANN

Yukai Zou et al. [85] established a complete technique based on ANN and NSGA-II for improving building performance by optimizing the design of typical architectural spaces. They offer a reliable styling for a popular classroom space using 30 design characteristics as a case study. The computation is roughly 2570-times faster than the typical optimization approach based on simulation. The overall objectives energy demand, thermal environment, and daylight environment of the cases were improved by 24.6%, 18.7%, and 14.2%, respectively, in the integrated solution.

2.8. GA, Harmony Search

Seyed Rouhollah et al. [86] examined the green roof system to reduce building energy consumption using the green roof concept and two genetic optimization and harmony search methods. The results revealed that green roofs save 3987 kWh or 89.5% more than solar panels. On the other hand, the amount of the saved energy per square meter of building per year (350 m^2), according to the building's usable infrastructure, is roughly 23.54 kWh for green roof usage, and 12.72 kWh for the use of solar panels. In addition, the green roof saves 15.94 kWh, and the solar panel saves 8.35 kWh in the cooling part, while the green roof saves 7.6 kWh, and the solar panel saves 4.36 kWh in the heating portion.

2.9. GA, PSO, Brute Force

A comprehensive study [87] was conducted to ideally choose building envelope components, heating, and cooling framework design. The simulation for this environment could decide the building configuration highlights that minimize the life cycle funds. They used the GA, the Particle Swarm Algorithm, and the sequential search measurement (GA, PSO, Brute Force). The results indicated that the ideal choice could decrease the life cycle costs relying on the atmosphere and the type of homes.

Harish Garg [88] investigated a mixed technique that performed the PSO with a GA scheme to solve any problem for constrained optimization requirements. The results indicated that this method gets the best solutions for any engineering problem to achieve the best objectives for any constraint.

2.10. Micro GA

Gange et al. [89] utilized a smaller scale micro-GA that uses a low percentage of the population compared with a typical GA to decrease the computational time of the simulation. This strategy merges a small-scale micro-GA calculation with an innate arrangement of inputs, including a unique 3d massing model and client particular execution objectives and changed exterior component development, geometry, and shading. The full building remains the same, while facade parts may differ. Such a method is used for the analysis of a boundless range of possible design circumstances utilizing a specific system for buildings.

2.11. GA-MOGA-II

Manzan et al. [90] used the advanced Multi-objective Genetic Algorithm (MOGA-II) for the external shading gadget to minimize the general essential energy in an office room. They considered the energy utilization for cooling, heating, and inner light. The enhancement was paired with the commodity radiance for sunshine figure estimation with an ESP-r energy production application. For every design, an alternate solution was acquired with a lessening of essential energy utilization. The results indicated that how MOGA-II optimization can be a capable tool for the planner.

2.12. GA-MIGA

OoKa et al. [91] proposed another perfect energy management approach for buildings. This strategy enhanced hardware limit and operational control arranging by utilizing an altered GA called Multi-Island Genetic Algorithm (MIGA), which included the GA distribution. The brilliant element of this technique was that the population of one group is divided into a few sub populaces called “Islands”. The results showed that the suggested strategy was adequately suited for determining the optimal program and could be connected to exceptionally complex energy frameworks with proper changes.

2.13. GA-Genetic Solver

Fanny et al. [92] created an advancement strategy managing a few goals as energy utilization, monetary cost, comfort, and the natural effect of the building. They used the Real Coded GA (Genetik Solver) that considers the multicriteria part of the building repair based on the Pareto principle to direct their answers. The solutions to improve restoration problems are viewed as a decisive approach given the GA (Genetik Solver). The retrofit choices of schools in France are streamlined to meet expressed energy focuses as inexpensively as could reasonably be expected.

2.14. GA, SPEA2

Pountney et al. [93] studied measurement for CO_2 emissions from buildings. The advancement issue inspected the exchange among carbon reduction and cost and some other factors as protection values, air density, framework efficiencies, lighting controls, and Photo-Voltaic (PV). The arrangement revealed the appropriateness of GAs to the assembled environment Marginal Abatement Cost (MAC) issue, a model was developed actualizing the Strength Pareto Evolutionary Algorithm (SPEA2). The SPEA 2 tool can give a more precise and nitty detailed arrangement of ideal solutions for buildings.

2.15. GA, SA

Romero et al. [94] streamlined the thermal conduct of a building by method for the best possible determination of some of its plan parameters, for example, thickness, warm properties, and reflectivity of dividers and rooftop utilizing a tropical building. They reduced overheating by changing technologies using two techniques for change, a Genetic Algorithm and Simulated Annealing (GA, SA). The findings showed how a suitable choice of design parameters might improve the warm conduct of the building.

Zhou et al. [95] displayed a portrayal of the execution of an enhancement algorithm inside EnergyPlus for building thermal capacity. A few parametric investigations were completed utilizing EnergyPlus with an interior enhancement module to decide the best control techniques for building thermal capacity stock in structures. The effects of the enhancement procedure are assessed under different working and configuration conditions. The best development approaches are found using Genetic and Simulated Annealing (GA, SA) schemes in assessment analysis.

Junghans et al. [96] examined hybrid single target building advancement calculation, which joins a transformative GA calculation with an altered SA calculation. Their findings revealed that the hybrid GA along with the updated SA offered solutions similar to the ideal worldwide in all the studies. The proposed algorithm, in this way, gives more solid results than the GA without the expansion of the adjusted SA.

Farshad Kheiri [97] investigated how hybridization with simulated annealing (SA) improved the GA's reliability, consistency, and robustness by different cooling strategies in the SA, to optimize the daylight and glazing in the building designs. Based on the mean values and variances of the objective function values, an analysis of the optimization methods' reliability, consistency, and robustness revealed that there is a significant difference between the hybrid GA/SA with higher temperature and the GA, where the hybrid algorithm performed better than the GA.

Harish Garg [98,99] investigated a new hybrid GA-GSA technique for analyzing the reliability of any system to raise the performance through uncertainties for data utilization. The results indicated that this method maximizes the availability parameters to increase the productivity of any design.

2.16. GA, PM

Turrin et al. [100] examined the advantages determined by consolidating Parametric Modeling and genetic (GA, PM) to accomplish an execution situated process in the building design, with a particular concentrate on architectural plan. They utilized a parametric model as a part of generative segments to advance a weighted entirety, sun-powered, and daylighting objectives. Recreations included Finite Element Analysis utilizing STAADPro and sunshine and light turn up in Ecotect. They investigated some auxiliary morphologies including multilayer NURBS frameworks and vaults. The parametric modeling upgrades an early structure of the plan issues by constraining the designer to deteriorate complex outline perspectives and their interrelations at an early stage.

2.17. GA, BPO

Attia et al. [101] compressed a study to reveal potential challenges and open entryways for joining advancement techniques within the Net Zero Energy Buildings (NZEB) outline. They utilized the GA technique of replication-dependent Building Performance Optimization (BPO), which is a procedure that aims for the determination of the ideal solutions from an arrangement of accessible options for a given outline as indicated by the execution standards for decision and evaluation. The measured quality, adaptability, and capacity to choose from a scope of advancement systems make the GA-BPO a robust scheme.

2.18. GA, MOEA, ANN

Asadi et al. [102] presented a multitarget advancement model utilizing GA and Artificial Neural Network (ANN) to evaluate innovation decisions in a building retrofit venture. This model joins the quickness of the ANN assessment with the improvement force of the Multi-objective Evolutionary Algorithm (MOEA) to build the GA-MOEA-ANN technique. A school building is utilized as a contextual analysis to display the practicability of the suggested plan and feature likely issues that may emerge. The study began with the individual streamlining of target capacities concentrating on building's qualities and execution: energy consumption, retrofit cost, and thermal discomfort hours.

2.19. GA, MDO

Lin et al. [103] introduced a theoretical foundation of an organizer masterminded Multidisciplinary Design Optimization (MDO) construction that identified as an Evolutionary Energy Performance Feedback Design (EEPFD). The capacity of EEPFD to quickly help in deciding the execution capability of different contending outlines for similar plan prerequisites that are increasingly suitable to applied engineering plan, which requests assorted qualities. Using the GA-MDO plan was all the more remarkable for a multidisciplinary configuration structure. EEPFD is created into an MDO framework that gives imperativeness execution as a contribution to affecting creators' decision making more easily and sooner than various approaches to manage the date.

2.20. GA, MOO

Inês Costa et al. [104] provided a comprehensive review that assesses the possibility of multi-objective optimization (MOO) using the Genetic algorithm (GA) for supporting the development of retrofitting techniques. They focused on the outcomes, challenges, method potential, and limitations for the 57 studies that were chosen. Due to time and efficiency problems, the results suggest that ideal retrofit solutions may need GA-mixed methods or modified GA. Heritage buildings, when defining qualitative objective functions is particularly difficult, have received little attention. They evaluated the study's merits and weaknesses as well as the gaps in the current literature and future research needs.

2.21. GA, HLGA

Chang et al. [105] proposed a strategy to discover the heuristic arrangements in the on-time choice stages for maintainable building outlines. This technique coordinates element programming and hereditary calculation into the configuration work process, by isolating outline criteria into three choice stages to lessen the multifaceted nature. For performance, they develop a parametric layout system with Hyper Learning Genetic Algorithm (HLGA) to give a graphical configuration environment, in which heuristic answers for every choice stage are discovered and consolidated. In every stage, the planner setups parameters identified with subrules and target abilities to improve by HLGA strategy.

2.22. GA, ANN

Jonathan et al. [106] studied two strategies for optimizing district energy management; one for optimizing district heat generation from a multi-vector energy center, and the other for directly controlling construction requirements through temperature set-points concerning heat generation. Several Artificial Neural Networks based on GA were used to forecast factors counting interest for structures, indoor temperature, and sun-based photovoltaic generation. Optimizing the district's heat generation resulted in a rise in profit of 44.88%, contrasted with a standard-based benchmark request approach. There was an additional achievement of about an 8.04% increase when the optimization directly controls a proportion of building demand.

Moazzami et al. [107] proposed an interesting hybrid strategy for everyday pinnacle load gauge dependent on Wavelet decomposition, neural network, and GA in Iran National Grid (ING). The ING maximum load information in the time horizon was used in this study from 4 February 2006 to 22 July 2011. In this exploration, the climate data for three major Iranian, Tehran, Tabriz, and Ahvaz towns with mild, cold, and hot climates were also used in the same period. The advised procedure with Generalized Feed Forward (GFF) based on ANN formed the smallest Mean Absolute Percentage Error MAPE of 1.2 percent. The MAPE of the suggested technique is 1.076% for the EUNITE test situation. Magnier et al. [108] studied multi-objective optimization in the construction using GA (NSGA-II) and ANN. Such optimization techniques are aimed primarily at reducing computational time. They used a Response Surface Approximation Model (RSA) to know the basic construction model conduct and then use it for the GA to evaluate people. The calculation time for GA optimization is reduced, a considerable amount of time is required to create baseline cases to train the ANN model for running the building simulations. The results were in good agreement with the data measured, while the relative errors were 3.7%, 3.4%, and 7.3% for heating, cooling, and fan monthly energy consumptions, respectively. Petri et al. [109] addressed the effectiveness of a modular-based optimization scheme for operating energy simulation and optimization to meet several energy-related goals. The modular system of optimization combined three distinct objectives where the ANN embraces the genuine enhancement process. The solution can tackle the variability in building dynamics and assist in developing energy-effective optimization plans for building managers. They provided the optimization scheme implemented based on power-saving requirements from the EU FP7 initiative—SportE2 (Energy Efficiency for Sports Facilities) and assessed the system's efficiency over several appropriate use-case scenarios.

This review includes all the GA varieties and their combinations to magnify the performance for solving many problems related to the decision for any parameters in the architecture design field. Also, we utilize other AI techniques to be combined with the GA to find the optimal solution to avoid the local minimum problem and get the best solution in the global minimum.

3. Results and Discussion

The primary goal of all GA-based model predictive control methods is to acquire future alternatives to an issue based on real and future model-based information. These choices ought to be made accessible in a coherent time and at a certain qualifying rate. A GA optimization with an extensive analysis was carried out in this context. Through the review analysis, a precise assessment proved a novel methodology for measuring the convergence precision of the alternatives. These values can be extrapolated to other comparable issues while looking for a perfect setpoint bend.

Table 1 presents the statistic basic summary for all the parameters and the schemes that help in the building design included in 72 studies.

Figure 2a shows that the most used techniques for optimization are GA, which represents 45.8%, and the NSGA-II, which represents 15.3%.

In Figure 2b, the most widely recognized objectives for these papers to utilize the GAs implementation for energy (65.3%), total cost, and the life cycle cost are 11.1%. The most common variables used are construction (15.3%), shaping (11.1%), and shading and HVAC (7%), as shown in Figure 2c.

Figure 2d shows that the greatest area of research is inside the entire structure (47.2%) and inside the envelope (16.6%), with the remaining 36.2% for the rest of the area searched as typical zone, indoor building, and others.

A total of 44.4% of papers focused on environmental applications, whereas 30.5% focused on energy applications, and the rest of applications represents 25.1%, as in Figure 2e.

Figure 2f shows the multi-objective functions used through the GA technique, which represents 53%, whereas the single-objective functions represent 44%, and 3% used the weighted sum (WS) function.

Figure 2g shows the software tools utilized in simulations; represented here is Energy-plus (18%), whereas papers that used no simulation tool represents 21.2%, and TRN-SYS is 13.8%.

Table 1. Basic statistic summary of the GA and its combinations.

	Scheme	Objective	Variables	Area of Research	Application	MO	Software	Country	Authors	Year	Ref.
1	GA	Energy, Comfort	Set Points	HVAC System	System	WS	TRN-SYS	China	Wang & Jin	2000	[38]
		Operational Cost	Constructions, Set Points, Flow Rate	Typical Zone	Environment, System, Continuous	N		UK	Wright & Farmani	2001	[40]
		Energy	Window dim.	Envelope	Form	N	DOE-2	USA	Caldas & Norford	2002	[41]
		Operational Cost, Comfort	Flow Rate, System Properties	HVAC System	System, Continuous	Y		UK	Wright et al.	2002	[42]
		Energy	Construction	Envelope	Environment	N	EXCALIBUR	UK	Coley et al.	2002	[44]
		Life Cycle Cost, Energy	Shape, Construction	Envelope	Environment, Form	WS	ASHRAE toolKit, LCA	Canada	Wang et al.	2003	[45]
		Energy	Control Parameters	HVAC	System	N	GA Simulation Tool	Theoretical study	Lu et al.	2005	[46]
		Life Cycle Cost, Energy	Shape, Construction	Envelope	Environment, Form	Y	ASHRAE toolKit	Canada	Wang et al.	2005	[47]
		Energy	Widow Dim., Shading, Set Points	Whole Building	Form	N	Energy +	Theoretical study	Wright & Alajmi	2005	[48]
		Energy	System Configuration	HVAC System	System	N		Theoretical study	Wright & Zhang	2005	[49]
		Life Cycle Cost, Energy	Shape	Envelope	Form	Y	GenOpt, DAKOTA	Canada	Wang et al.	2005	[50]
		Energy	Plant Capacities, Operational Strategy	CHP System	Renewable	N		Theoretical study	Tanaka et al.	2007	[51]
		Life Cycle Cost, Energy	Constructions, Ventilation, Renewable	Whole Building	Environment, Renewable	Y	TRN-SYS, COMIS	Belgium	Verbeeck & Hens	2007	[52]
		Day light	Constructions, Window Dim., Shading	Envelope	Environment, Form	N	Radiance	japan	Torres & Sakamoto	2007	[53]
		Energy, Total Cost	Shape, Construction, Shading	Whole Building	Environment, Form	N	CHEOPS	Tunisia	Znouda et al.	2007	[54]
		Construction Cost, Energy	Layout, shape, construction	Whale Building	Form	Y	DOE-2	Portugal	Caldas	2008	[55]

Table 1. *Cont.*

Scheme	Objective	Variables	Area of Research	Application	MO	Software	Country	Authors	Year	Ref.
	Energy	System Configuration, Operation Strategies	HVAC System	System	N		Theoretical study	Wright et al.	2008	[56]
	Total Cost, Energy	Plant Capacities	CHP system	Renewable	Y		Theoretical study	Kayo & Ooka	2009	[57]
	Energy	Window Grid	Whole Building	Form	N	Energy +	USA	Wright & Mourshed	2009	[58]
	Life Cycle Cost	Shade, Construction	Whole Building	Environment, Form	N	DOE-2	USA	Tuhus, Dubrow	2010	[59]
	Energy	Constructions	Envelope	Environment	N	Matlab	India	Sahu et al.	2012	[61]
	Construction cost, Humidity	Humidity, materials, location and Thickness	Humidity Level	Environment	Y	transient	Theoretical study	Huang et al.	2012	[62]
	Energy	HVAC Zone	Whole Building	System	N	DOE-2	Montreal	Stanescu et al.	2012	[63]
	building energy consumption	building profiles and HVAC configurations	Whole Building	Energy	Y	Energy+	Spain	Petriet al.	2014	[109]
	Integrated Analysis of Building Designs	component quantity, initial construction cost, labor cost, and equipment cost, daily productivity, environmental emissions	Whole Building	Energy	N	Energy+	USA	Inyim P	2013	[79]
	Energy	construction cost, such as material cost, labor cost, and equipment cost, daily	Whole building	Energy	N	Matlab	Canada	Ahmadi et al.	2010	[71]
	Energy	Temp& CO_2 concentration & illumination	Whole building	Energy	N		Malaysia	Shaikh et al.	2014	[72]
	Index of distribution	building layout	Whole building	Environment	N	ArcGIS Desktop	China	Tong et al.	2016	[73]
	Energy	window shading& glass thickness &outdoor air flow	Whole building	Energy	N	Energy+	Spain	Yang et al.	2014	[74]

Table 1. *Cont.*

	Scheme	Objective	Variables	Area of Research	Application	MO	Software	Country	Authors	Year	Ref.
		Cost of Greening	Colling effect, connectivity, cost	Typical zone	Environment	N	(NSGAII,)	Korea	Yoon et al.	2019	[76]
		window to wall ratio, form finding	solar radiation, Exterior wall, Interior floor, Glazing type, Zone	Whole building	window to wall ratio	Y	SPEA-2	Iran	Zahra Jalali et al.	2019	[77]
2	GA, Monte-Carlo	Energy	load power& usage rate & photovoltaic &PV&generators	Whole building	Energy	N	NZEBs	Paris	Garshasbi et al.	2016	[78]
3	GA (NSGA-II)	Life Cycle Cost, Energy	Constructions, Heat Recovery	Envelope	Environment	Y	Genopt, IDA ICE	Finland	Palonen et al.	2009	[64]
		Cons. C., Energy, Comfort	Controls, Constructions	Whale Building	Environment, Continuous	Y	TRN-SYS, COMIS	France	Chantrelle et al.	2011	[65]
		Construction cost, CO_2	Constructions, Glazing systems	Whole Building	Environment, Form, System, Renewable	Y	TRN-SYS	Finland	Hamdy et al.	2013	[66]
		Construction cost, Energy	Shape, Constructions, systems, renewable	Typical Zone	Environment, Form, System, Renewable	Y	SAP	Theoretical study	Evins et al.	2012	[67]
		Life Cycle Cost, Energy	Constructions, Glazing systems, Renewables	Whole Building	Environment, Form, System, Renewable	Y	IDA ICE	Finland	Hamdy et al.	2012	[68]
		Total Cost, CO_2, Comfort	Renovation strategies, Constructions	Whole Building	Environment, System	Y	Energy +	UK	Jin & Overend	2012	[69]
		Total Cost, Energy	Shape, Constructions, systems, renewable	Whole Building	Environment, Form, System, Renewable	Y	SAP	UK	Evins et al.	2012	[70]
		Energy, Comfort	Day Light, ventilation	Indoor Building	Environment, System	Y	Energy +	China	Wei Yu et al.	2014	[32]
		Energy, Comfort	temperature set-points, indoor thermal comfort	Whole building	Energy	Y	OpenStudio & EnergyPlus	Spain	Germán Ramos et al.	2019	[80]
		Envelope Energy Load, Air conditioning system	Window Dim., Sunshade (style, board length), Glass material, Glass curtain material, Roof	Whole building	Energy, Comfort	Y	MOBELM	Taiwan	Yu-Hao Lin et al.	2020	[81]

Table 1. *Cont.*

	Scheme	Objective	Variables	Area of Research	Application	MO	Software	Country	Authors	Year	Ref.
4	GA (PA-NSGA-II), Fuzzy, AHP	Energy, Comfort	Indoor Temp & Indoor relative humidity& co2 concentration	Whole building	Energy, Comfort	Y	Design-Builder	China	Yifang Si et al.	2019	[82]
5	GA, PA, NSGA II	Energy, Construction cost	Constructions, Lighting control, Ventilation	Whole Building	Environment, Continuous	Y	IDA ICE	Finland	Salminen et al.	2012	[83]
6	GA, PSO, BruteForce	Life Cycle Cost	Shape, Construction	Building	Environment, System, Continuous	N	DOE2	USA	Bichiou and Krarti	2011	[87]
7	GA (Micro)	Daylight, Glare	Constructions, Shading	Envelope	Environment	Y	Light Solve Viewer	Boston	Gagne & Anderson	2011	[89]
8	GA (MOGA-II)	Energy	Shading	Envelope	Environment	N	ESPr, Radiance	Italy	Manzzn & Pinto	2009	[90]
9	GA (MIGA)	Energy, CO_2	Plant Capacities, Operational Strategies	CHP system	Renewable	N		Japan	Ooka & komanura	2009	[91]
10	GA (Genetik Solver)	Total Cost, Energy	Constructions, Lighting	Envelope	Environment, Continuous	Y	TRNSYS	France	Pernod et al.	2009	[92]
11	GA (SPEA2)	Construction cost, CO_2	Constructions, Lighting, control system	Whole Building	Environment, System, Renewable	Y	SBEM	UK	Pountney	2012	[93]
12	GA, SA	Comfort	Constructions	Envelope	Environment	N		Venezuela	Romero et al.	2001	[94]
		building façade	Type of glazing, amount of insulation, air-tightness of the façade, and geometry of the shading system.	Whole Building	Environment	Y	Energy+	Chicago	Junghans et al.	2015	[96]
		Energy	Set Points	Whole Building	Continuous	N	Energy +	Theoretical study	Zhou et al.	2003	[95]
13	GA, PM	creation of design solutions& knowledge extraction from the generated solutions	design and performance	passive solar behavior& HVAC	Environment	Y	ParaGen	Theoretical study	Turrin	2011	[100]

Table 1. *Cont.*

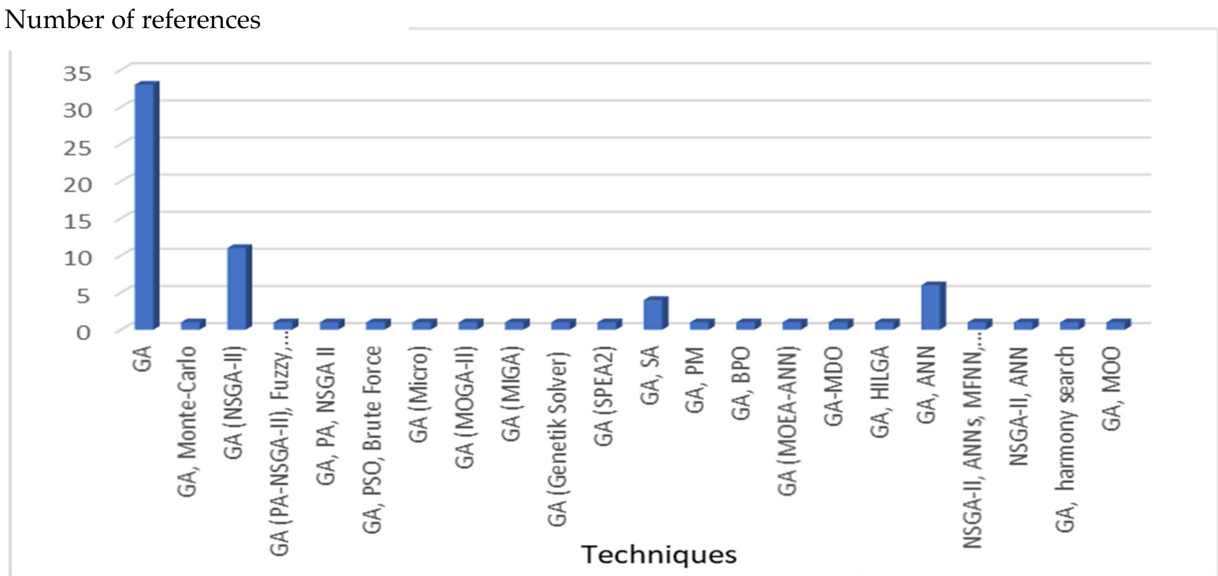
	Scheme	Objective	Variables	Area of Research	Application	MO	Software	Country	Authors	Year	Ref.
14	GA, BPO	Energy	System Configuration	HVAC System	Environment, System	Y	GenOpt	Theoretical study	Shady et al.	2013	[101]
15	GA (MOEA-ANN)	building retrofit	The external wall insulation materials; roof insulation materials; windows type; solar collectors' type; HVAC systems.	CHP system	Energy	Y	TRNSYS	Portugal	Ehsan Asadi et al.	2014	[102]
16	GA-MDO	performance boundaries	energy domain and geometric exploration	Typical zone	Energy	Y	Revit	Theoretical study	Shih-Hsin Lin	2014	[103]
17	GA, HILGA	sustainable architecture design	construction materials & construction costand energy consumption	Whole Building	Energy	Y	DIVA 2.0	Taiwan	Mei-Chih et al.	2014	[105]
18	GA, ANN	Energy, CO_2 emissions	Thermal capacity, electrical capacity, thermal storage, indoor temp.	Typical zone	Energy	Y	EnergyPlus	UK	Jonathan R. et al.	2019	[106]
		Energy	Indoor Temp & Air flow rate	Typical zone	Energy	N	EnergyPlus	Theoretical study	Petri et al.	2014	[109]
		Energy	Load demand & weather-variable	Typical zone	Energy	N		Iran	Moazzami et al.	2013	[107]
		Operational cost	Supply & Returns flows & Temp.	HVAC system	System	N		China	Chow et al.	2002	[43]
		Energy	Water Temp.	HVAC system	System	N	Energy +	New Belgrade	Congradac et al.	2012	[60]
		Energy	HVAC& building envelope	Typical zone	Energy	N	TRNSYS	Canada	Magnier et al.	2010	[108]
19	NSGA-II, ANNs, MFNN, MOPSO, MOGA	Energy, Comfort	Opaque walls, Glass walls, Shading, Air change rate	Whole Building	Energy	Y	TRNSYS	Morocco	Badr Chegari et al.	2021	[84]

Table 1. *Cont.*

	Scheme	Objective	Variables	Area of Research	Application	MO	Software	Country	Authors	Year	Ref.
20	NSGA-II, ANN	Energy, Comfort, daylight environment	orientation, space length, space dimensions, shading device, outdoor sidewall, corridor sidewall, outdoor side window, corridor side window	Typical zone	Energy, Environment	Y	Geatpy	China	Yukai Zou et al.	2021	[85]
21	GA, harmony search	Energy	None	Whole Building	Energy	Y	None	Iran	Seyed Rouhollah et al.	2020	[86]
22	GA, SA, H-EA	Energy	Window height, Window sill, Number of slats, Angle of slats, Projection of slats	Typical zone	Energy	Y	Grasshopper	Texas	Farshad Kheiri	2021	[97]
23	GA, MOO	Energy, Cost	all genes	Whole Building	Energy	Y	EnergyPlus, TRNSYS	Theoretical study	Inês Costa et al.	2019	[104]

The GA techniques are built as a theoretical solution to some problems like optimization at 20.8%, but most countries that used these techniques are UK (11.1%) and China (8.3%); see Figure 2h.

Figure 2i shows that the algorithms are widely used during the last 21 years, where the highest numbers of research based on the GA schemes are in 2012, representing 13.8%, and in 2014 (12.5%), whereas the least were in 2000, 2006, and 2015 which are 1.4%. There were more worries about the depletion of energy resources and the enhancement of indoor comfort as well as the enhanced time spent in construction. Building activity requires more energy in large inhabitance rooms in summertime government structures because most energies were consumed to make the indoor environment comfortable.



(**a**)

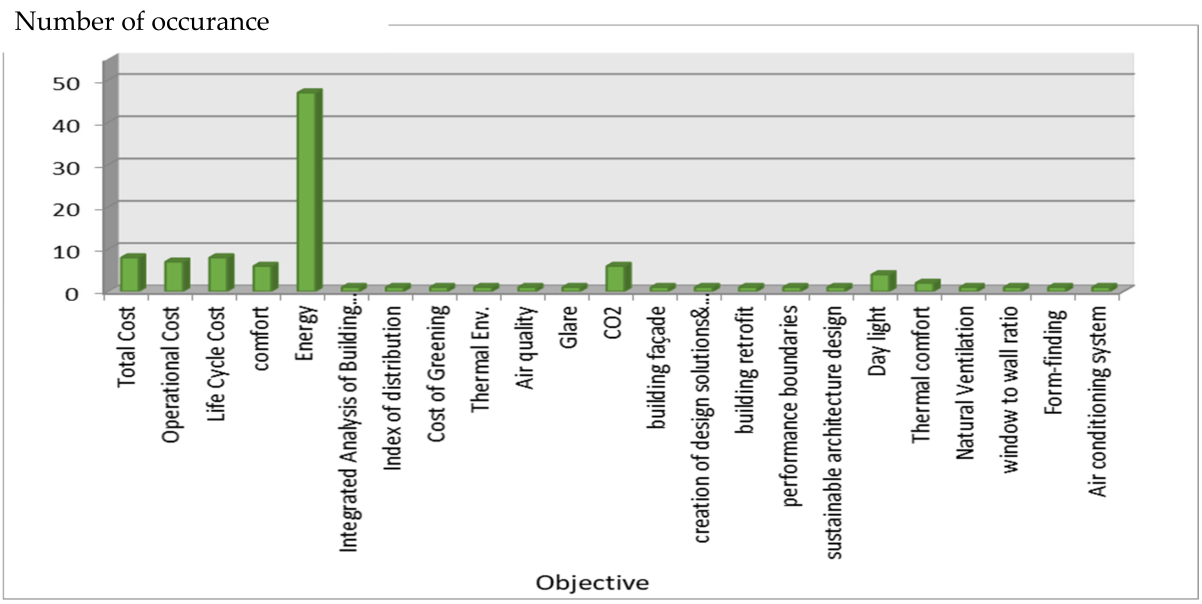


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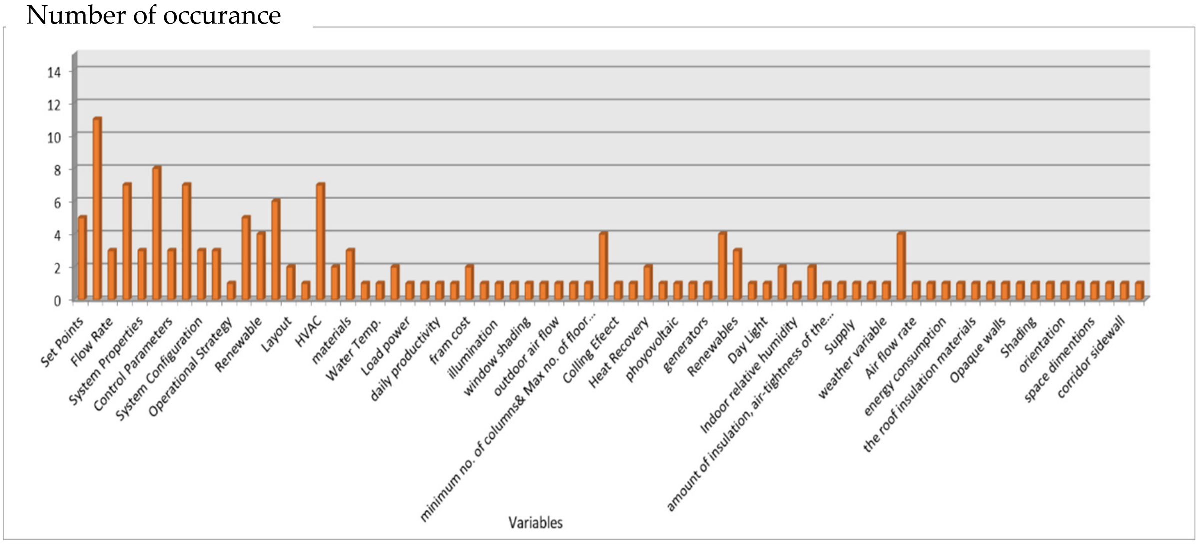
Figure 2. *Cont.*



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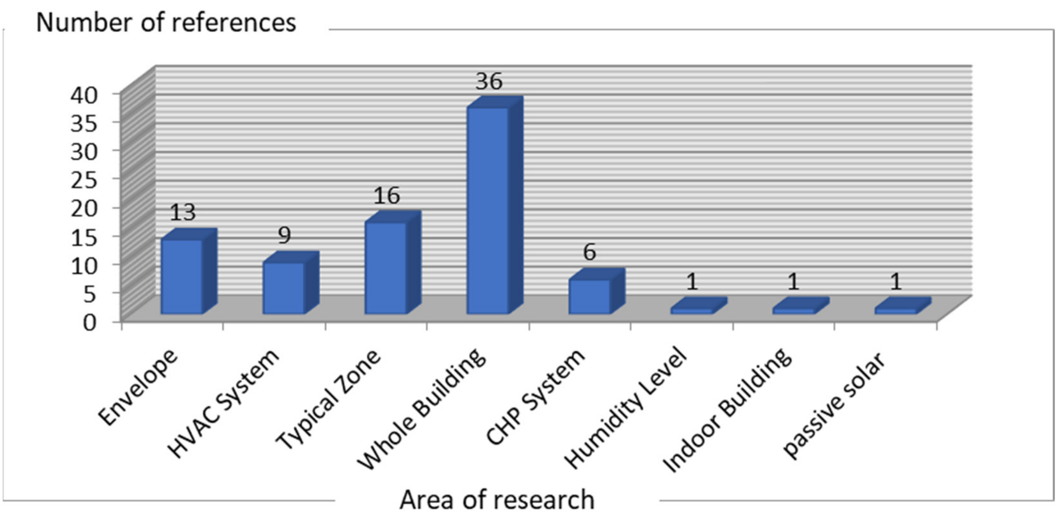

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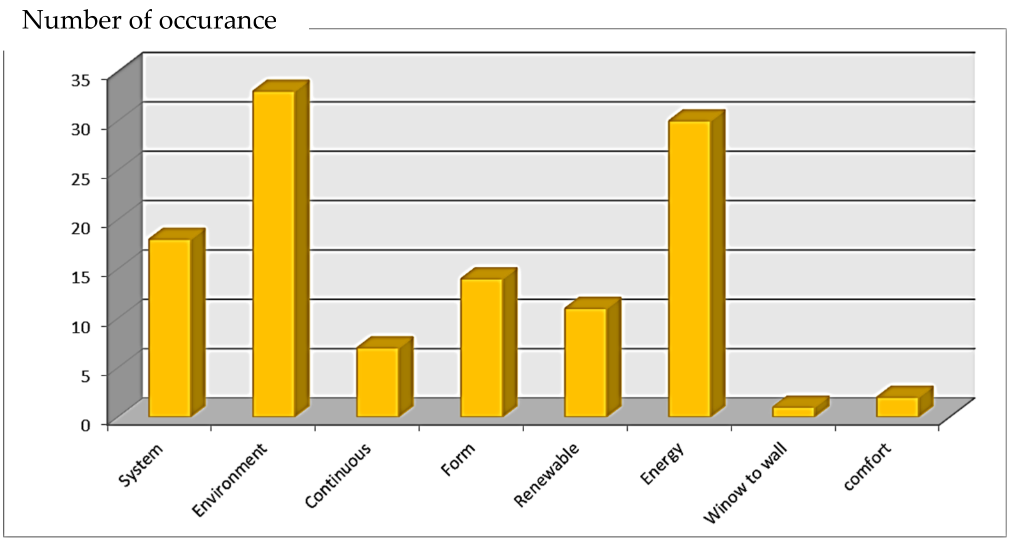

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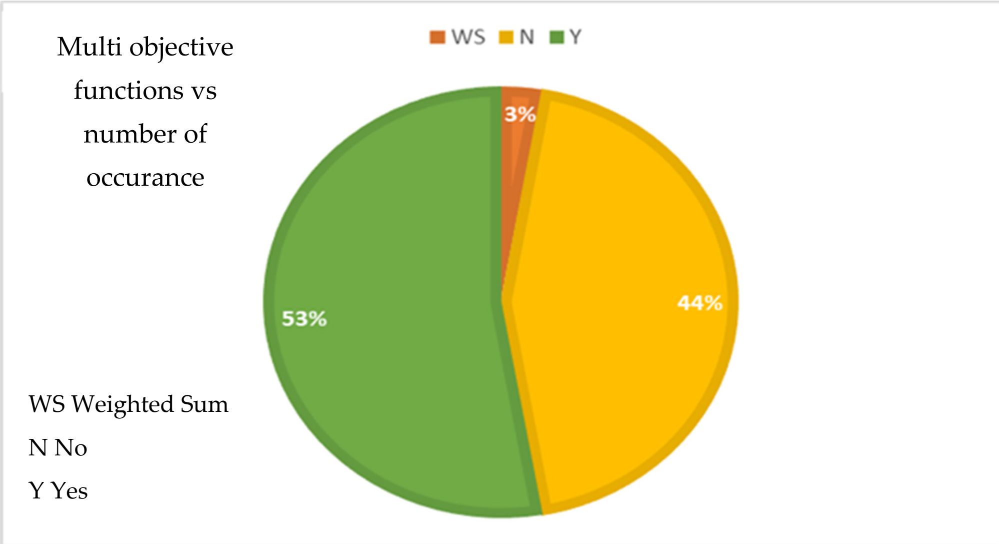

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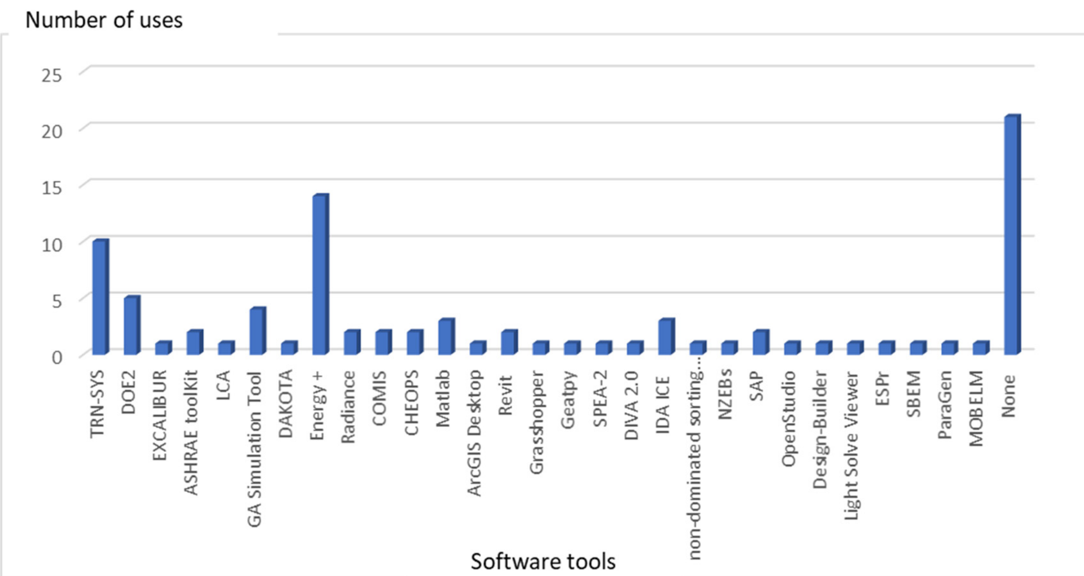

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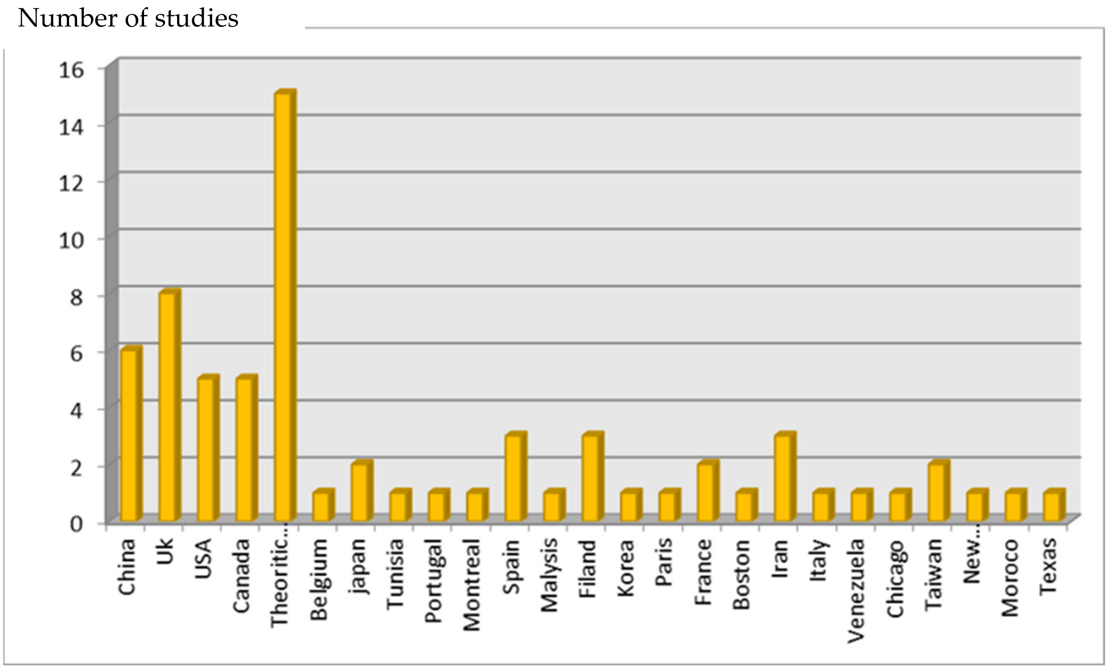
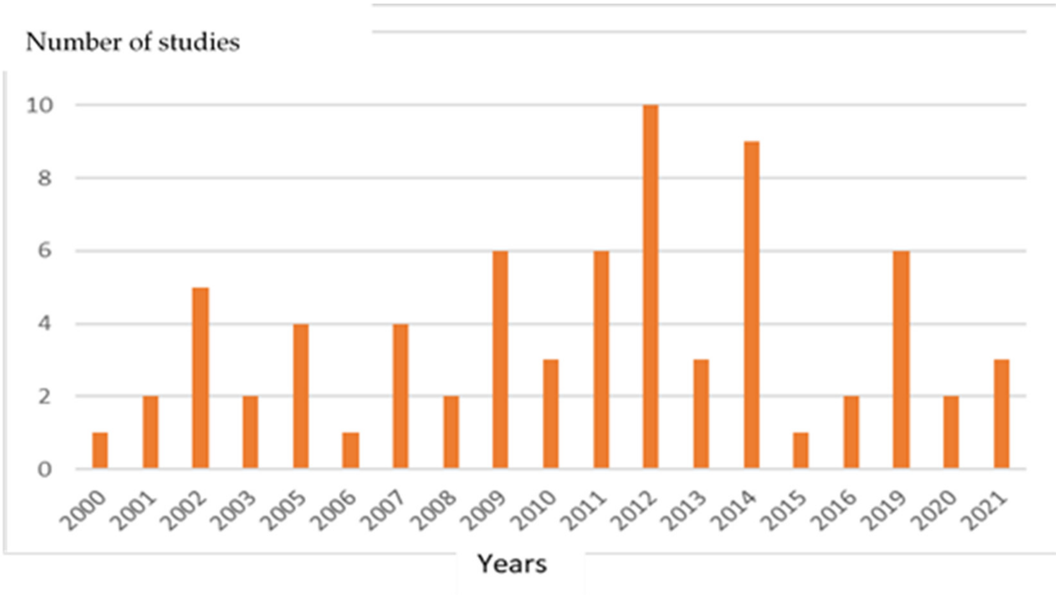
Figure 2. *Cont.*



(**h**)



(**i**)

Figure 2. GA statistical information. (**a**) Collection techniques of GA; (**b**) GA objectives; (**c**) variables of genetic scheme; (**d**) area of research; (**e**) applications based on GA; (**f**) GA multi-objective functions; (**g**) investigation of GA as indicated for countries; (**h**) investigation of GA as indicated for countries; (**i**) study of GA according to years.

In Table 2, we extracted the state-of-art research articles to investigate the tools, and the simulation processes were used to solve the optimization problems and their parameters, which affect the buildings' design and decision-making processes. Table 2 shows that the algorithm has the highest impact on the decision-making process is the NSGA-II technique in the field of building design. Also in Table 2 are many parameters of the NSGA-II technique, which can be variated as population size, iteration numbers, crossover section, and mutation section based on the objective and the constraints in each optimization problem.

Table 2. Extraction of data studies for analysis, and GA parameters.

Authors/Publisher/Journal	Reference Number	Optimization Tool	Simulation Tool	Objective Function	Constrains	Parameters	Parameters Values	Population Size	Iteration No.	Crossover Section	Mutation Section	Case Study Location	Research Goal (Scope)
Eun Joo Yoon et al. Urban Forestry & Urban Greening Elsevier 2019	[76]	NSGA II	IDM	- cooling effect (Maximum) - connectivity (Maximum)	cost (Minimum)	Cooling effect	location, Area, type of green spaces	30	30	1	2	general	residential building
						Connectivity	Distance of green spaces, Area, type of green spaces						
						Cost	$						
Germán Ramos Ruiz et al. Energies mdpi 2019	[80]	NSGA-II	OpenStudio, EnergyPlus	- energy consumption (Min.) - thermal comfort (Maximum)	Algorithm computational time (Minimum)	temperature set-points	12 °C−17 °C	User define	User define	binary	polynomial	Spain	residential building
						indoor thermal comfort	Temp						
Yifang Si et al. Intelligent Buildings International Taylor & Francis 2019	[82]	GA(PA-NSGA-II), Fuzzy, AHP	Design-Builder	- indoor comfort (Maximum) - energy consumption (Minimum)	indoor CO_2 concentration (Minimum)	The indoor air temperature	24 °C–28 °C	100	200	none	none	China	Public building
						relative humidity	30%–70%						
Jonathan Reynolds et al. Applied Energy Elsevier 2019	[106]	GA + ANN Applied Energy	EnergyPlus	- energy consumption (Minimum) - CO_2 emissions (Minimum)	none	thermal capacity	207 KW	200	100	1	1	UK	district
						electrical capacity	138 KW						
						thermal storage	95%						
						indoor temperature	23 °C–28 °C						
Zahra Jalali et al. Taylor & Francis Science and Technology for the Built Environment 2019	[77]	GA	SPEA-2	- window to wall ratio - Form-finding	none	solar radiation	Cooling Load KWh/m^2, Heating Load KWh/m^2	50	100	Crossover rate = 0.8	Mutation probability = 0.1	Iran	office building
						Exterior wall	brick, concrete						
						Interior floor	Acoustic tile Ceiling air space resistance						
						Glazing type	Triple						
						Zone	Rotation, Width, Length, Height						
Inês Costa Carrapiço et al. Energy & Buildings Elsevier—review paper 2019	[104]	GA-MOO	EnergyPlus, TRNSYS	- retrofit cost (Minimum) - Energy (Minimum)	retrofit time (year)	all genes	decision variables	105–161	Max. populations	Pc	Pm	general	general building

Table 2. *Cont.*

Authors/Publisher/ Journal	Reference Number	Optimization Tool	Simulation Tool	Objective Function	Constrains	Parameters	Parameters Values	Population Size	Iteration No.	Crossover Section	Mutation Section	Case Study Location	Research Goal (Scope)
Yu-Hao Lin et al. Sustainable Cities and Society Elsevier 2020	[81]	NSGA-II	MOBELM	- Envelope Energy Load (Minimum)	construction cost (Minimum)	Window (number, width, and length)	Number = (1, L); width = [6 × 20 cm. 14 × 20 cm]; length = [6 × 20 cm.14 × 20 cm]	200	200	0.85	0.05	Taiwan	government buildings
				- air conditioning systems (Minimum)	CO_2 emissions (Minimum)	Sunshade (style, board length)	style = (1 for horizontal,2 for vertical, and 3 for grid); board length = (3 × 20 cm.18 × 20 cm)						
						Glass material	material = (1 for Single -layer 11 for off-line glass with blue)						
						Wall material	material = (1, 13) Wmi						
						Glass curtain material	material = (1, 14) Gcmi						
						Roof material	material = (1, 14) rmi						
Seyed Rouhollah et al. PAIDEUMA JOURNAL University of Maine 2020	[86]	GA, HSA	None	building energy consumption	None	Air temperature	2.44 °C –5.88 °C	60	100	0.95	0.50%	Tehran (Iran)	Residential Building
						Sun radiation	3.8 W/m^2–4.7 W/m^2						
						Rain	238.8 mm						
Badr Chegari et al. Elsevier Energy & Buildings 2021	[84]	ANNs, MFNN, NSGA-II, MOPSO, MOGA	TRNSYS software	- energy performance of residential buildings (Maximum) - indoor thermal comfort (Maximum)	computation time (Minimum)	Opaque walls,	- The upper & lower limit of heat transfer	25–100	25–100	0.9	0.50%	Marrakech (Morocco)	Residential building
						Glass walls	single glazing up to 5 levels						
						Shading	Low at 0%, upper limit at 100%						
						Air change rate	lower limit, upper limit (defined according to the reference building situation						

Table 2. *Cont.*

Authors/Publisher/Journal	Reference Number	Optimization Tool	Simulation Tool	Objective Function	Constrains	Parameters	Parameters Values	Population Size	Iteration No.	Crossover Section	Mutation Section	Case Study Location	Research Goal (Scope)
Yukai Zou et al. Elsevier Energy Reports 2021	[85]	ANN, NSGA-II	Geatpy	- energy demand - thermal environment - daylight environment	the universality of the research, (the architects face reference value to similar situations)	orientation	0°, 360°	100	10,000	1	1	Guangzhou (China)	classroom, universality
						space length	Length, width, height						
						corridor width	1.5 m, 4.0 m						
						shading device	Type, dimension						
						outdoor sidewall brick	Conductivity, density, specific heat, thickness, insulation, absorptance						
						corridor sidewall brick	Conductivity, density, specific heat						
						corridor sidewall	thermal insulation, thermal insulation thickness, solar absorptance						
						outdoor side window	-to-wall ratio, U-value, SHGC, VT						
						corridor side window	-to-wall ratio, U-value, SHGC, VT						
Farshad Kheiri Indoor and Built Environment SAGE 2021	[97]	GA, SA, H-EA	Grasshopper	energy-efficiency	- Window height (0.40 m–2.20 m) - Window sill (0.20 m –2.40 m) - Number of slats (1–20) - Angle of slats (0°–89°) - Projection of slats (0.10 m–1.40 m)	Office geometry	Length, width, height, window width,	220	250	0.9	0.043	Houston (TX)	single office room
						Material reflectance	Wall, Ceiling, Floor, Shading, Ground,						
						Glazing (Double Pane Low E) Properties	SHGC, U-value, Transmittance						

4. Conclusions and Future Work

This paper presented a complete state of art review for the current late AI-based applications (2000–2021) utilizing methodologies, innovations, strategies, and models that were utilized in green building engineering to examine ideal green arrangements and models. The paper proved that there is an increasing trend of interest in optimization. The builders and industries are realizing the high potential of GA approaches, such as GA schemes and GA-NSGA-II approach, because they are confronting more stringent difficulties than any other time recently, with an expanding interest for outlines to perform well environmentally and monetarily.

The GA-incorporated strategies are relevant, compelling, and proficient in the field of green/economical structure across a wide scope of examination fields and environmental problems related to green architecture/building. The GA technique, when combined with other techniques/approaches/models, such (NS), PA, PSO, BF, MOEA, MOGA, MIGA, GS, SPEA, SA, PM, BPO, ANN, MIDO, and HL, yields a more convenient approach for many practical quantitative and/or qualitative applications, such as quantitative evaluation model for sustainable community construction and low-carbon development effectiveness. Based on the current survey, these recent technologies are widely used in developed countries such as UK, China, the USA, Canada, Portugal, France, and Italy, while in developing countries it is still not widely used.

Because of the worldwide sustainability drive, the increasing trend in power efficiency construction studies is anticipated to continue. This makes energy data monitoring and forecasting of energy information in real-time relevant and essential in this area.

This paper includes all the GA varieties and its combinations to magnify the performance for solving many problems related to the decision of any parameters in the architecture design field. AI techniques can be combined with the GA to find the optimal solution to avoid the local minimum problem and get the best solution in global minimum that maximizes optimality.

Future Work: we could study some of the new AI techniques like Machine Learning (ML) and Deep Learning (DL) to build a data set related to the design building method to get a model to solve more complex problems.

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Nomenclature

AI	Artificial Intelligence
ANP	Analytic Network Process
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Network
AHP	Analytic hierarchy process
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
BPO	Building Performance Optimization
BIM	Building Information Modeling

BKP	Back-propagation
RBFNN	Radial-Basis-Function Neural Network
CCHP	Combined Cooling, Heating, and Power
CHP	Combined Heat Power
COMIS	Multizone Air Flow Modeling
CSW	compressed shopper waste blocks
CBM	Conceptual Building Modeler
DOE-2	Freeware building energy analysis program
DEA	Data Envelopment Analysis
EcoTect	Building energy analysis tool
EUFP7-SportE2	Energy Efficiency for Sport Facilities
Energyplus	Energy analysis and thermal load simulation program
EKB	Egyptian Knowledge Bank
ESP-r	Simulation Program.
EUL	Egyptian Universities Librar
eunite	European network on intelligent technologies
EEPFD	Evolutionary Energy Performance Feedback for Design
Envelope	Building envelope
Form	An architectural design, stylish, structural with sustainability influences
GA	Genetic Algorithm
GAF	genetic algorithm using fuzzy system
GenOpt	Generic Optimization Program
GENE_ARCH	Generative Design System uses adaptation to shape energy-efficient, sustainable architecture solutions
GNN	Generalized Neural Network
GFF	Generalized Feed Forward
H-EA	Hybrid Evolutionary Algorithms
HAS	Harmony Search algorithm
HQENN	Hybrid Quantized Elman Neural Network
HPSO	Hybrid Particle Swarm Optimization
HLGA	Hybrid Learning Automata Genetic Algorithm
HVAC	Heating, Ventilation, and Air Conditioning
IDA ICE	IDA Indoor Climate and Energy (simulation tool for making the whole building energy)
IDM	Interactive Decision Maps technique
IOD	Index of Distribution
IVCGA	incorporated The Interactive and Visual Genetic Clustering Algorithm
KPI	Key performance indicators
In. of dis.	Index of distribution
ING	Iran National Grid
Int. An. Of B. D.	Integrated Analysis of Building Design
qu	Air quality
retrofit	Building retrofit
F.	Building façade
B. E. cons.	Building Energy consumption
Cr. of D. sol.	Creation of Design solution
Cons. C.	Construction cost
Of green.	Cost of greening
D. G.	Daylight Glare
E.	Energy
Ex. Eff.	Exegetic efficiency
Hum.	Humidity
LEED	Leadership in Energy & Environmental Design
LibGen	Library Genesis scientific papers
LT	Lighting and Thermal
LS	least error Squares
LAVF	least Absolute Value Filtering

MAC	Marginal Abatement Cost
MO	Multi-objective
MOPSO	Multi-objective Particle Swarm Optimization
MFNN	Multilayer Feedforward Neural Networks
MIGA	Multi-Island Genetic Algorithm
MWh	Megawatthour
MOEA	Multi-objective Evolutionary Algorithm
MDO	Multidisciplinary Design Optimization
MOGA-II	Multi-objective Genetic Algorithm-II
MPC	Simulation-based Model Predictive Control procedures
MAPE	Mean absolute percentage error
NSGA-II	Nondominated Sorting Genetic Algorithm
NURBS	Nonuniform Rational Basis spline A Number of Structural Morphologies with Multi-layer
NZEB	Net Zero Energy Buildings.
NN-SVM	Neural Network with Vector Support Machine
PA	Pareto Archive
PC	Personal Computer
PM	Parametric Modeling
PV	Photovoltaic
PSO	Particle Swarm Algorithm
Ren	Renewable energy
RMSE	Root-Mean-Square comparative mistake
RGA	Real-valued Genetic Algorithm
RTE	Réseau de Transport d'Électricité (Electricity Transmission Network)
RSA	Response Surface Approximation Model
SAP	Standard Assessment Procedure
SimulEICon	A Multi-objective Decision-Support Tool for Sustainable Construction
STAAD Pro	Structural Analysis & Design software
SPEA2	Strength Pareto. Evolutionary Algorithm
SA	Simulated Annealing
SGAS	Sorting Genetic Algorithm strategy
SCADA	Supervisory Control and Data Acquisition
SHGC	Solar Heat Gain Coefficient
SVM	Support Vector Machine
TRNSYS	TRaNsient SYstem Simulation Program
TC	Thermal Comfort
VT	Visible Transmittance
WS	Weighted-Sum
ZigBee technology	wireless technology to meet the distinctive requirements of low-cost, low-power wireless IoT networks as an accessible worldwide standard
Kn. Ext. of sol.	Knowledge extraction from the solution
L.	Lighting
Mo.	Multi Objective
N. V.	Natural Ventilation
Oper. C.	Operational cost
P. boun.	Performance boundaries
Sus. Arch. D.	Sustainable Architecture Design
T. C.	Total Cost
Th. Env.	Thermal Environment
Y. N.	Yes, No

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