Genetic Algorithm for Building Optimization - State-of-the-Art Survey

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ABSTRACT
Model-based building operation optimization can be used to reduce building energy consumption, so as to improve the indoor environment quality. Genetic Algorithm (GA) is one of the commonly used optimization algorithms for building applications. To provide readers up-to-date information, this paper attempts to summarize recent researches on building optimization with GA. Firstly, the principle of GA is introduced. Then, we summarize the literatures according to different categories, including applied system types and optimization objectives. We also provide some insights into the parameter setting and operator selection for GA. This review paper intends to give a better understanding and some future directions for building research community on how to apply GA for building energy optimization.

CCS Concepts
• Applied computing → Physical sciences and engineering → Engineering → Computer-aided design

Keywords
Building; Energy; Optimization; Genetic algorithm.

1. INTRODUCTION
Buildings accounted for about 40% of total primary energy consumption in the United States, about 41.4% in China [1], and about one-third in the world [2]. In order to reduce energy consumption and mitigate the environmental problems associated with energy generation, it is essential to find effective strategies to reduce building energy consumption. Although some research reveals that there is a potential to reduce building energy consumption by about 30%-40% [3], it is difficult to achieve that potential in practice because buildings are non-linear systems and their energy consumption depending on various factors, such as weather, orientation, occupant behavior, etc.

In recent year, a large number of optimization methods have been applied to improve the building energy efficiency [4]. The commonly used optimization algorithms include GA, particle swarm optimizing (PSO), simulated annealing (SA), generalized pattern search methods (GPS), coordinate search, and Hooke–Jeeves (HJ) algorithms. Those methods can be generally divided into the following categories: evolution algorithms, derivative-free search methods and hybrid algorithms [5, 6].

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On one hand, the selections of the optimization methods are highly depend on the characteristics of the problem domain. On the other hand, the properties of an optimization algorithm are also crucial for the selection. As for GA, it simulates "the survival of the fittest" of Darwin evolution and generates useful solutions for optimization through a series of natural selection operations, such as selection, crossover and mutation [7]. In addition, there are some notable advantages distinguishing it from other optimization methods [8, 9]:

1) It adopts stochastic operators instead of deterministic rules to search for a solution that will allow GA to avoid local optimum.
2) It considers many points in the searching space simultaneously, not a single point, to deal with large parameter spaces.
3) It is publicly available and its codes can be easily implemented.
4) It does not require a continuous objective function. Thus, it can handle both discrete and continuous parameters. This is especially important for building applications since both types of parameters are common in building energy performance models.
5) It can find multiple Pareto solutions for a multi-objective optimization problem in one run.

Because of the above mentioned attractive features, the GA is well-suited for the discontinuous and non-linear problem in building optimization. Therefore, GA, as the most recognized technology in building performance analysis, has been employed to handle many optimization problems. GA accounts for about 29%-40% among all the building optimization methods mentioned in literature [2, 6, 10]. However, the application of GA for building energy optimization has not been thoroughly studied and reported. This paper aims to fill this gap by providing a detailed literature review of GA applications in buildings.

2. OVERVIEW OF GA
GA is a heuristic search inspired by natural selection. A simple GA work flowchart is illustrated in Figure 1. Firstly, it starts from problem analysis to determine the solution domain and fitness function definition to evaluate the solution domain. Secondly, a binary or real coding is applied to represent each candidate

solution. Thirdly, an initial population is randomly generated. Then, genetic operators including selection, crossover and mutation are introduced for breeding new solutions. Finally, through repetitive application of genetic operators and fitness evaluation, a global optimal solution will be ultimately obtained until GA meets the termination criteria.

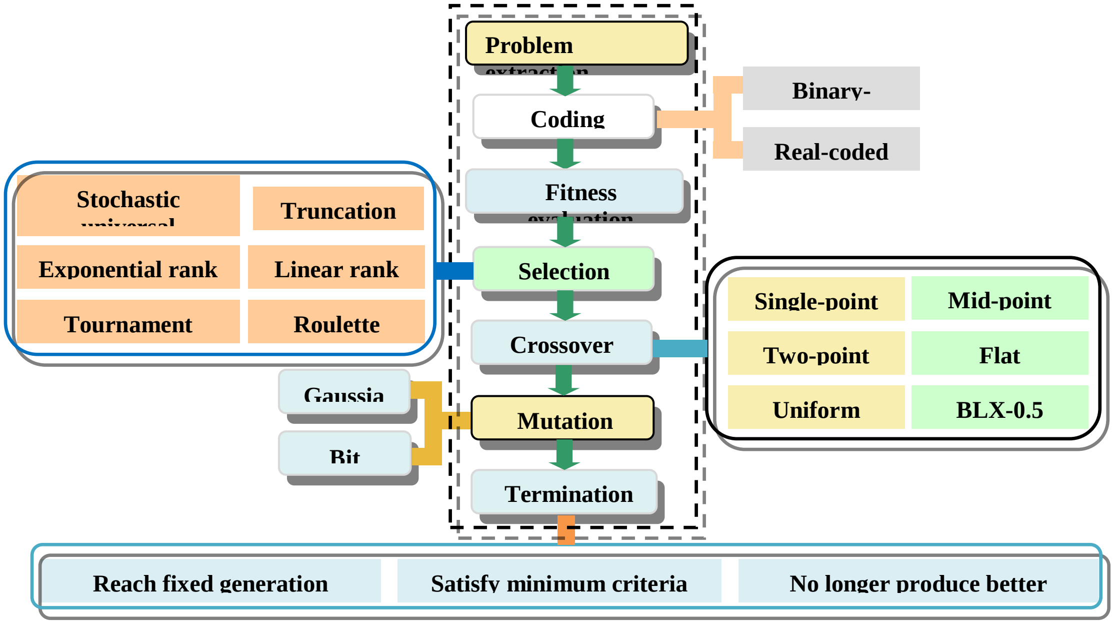

Figure 1. Flowchart of GA procedure. Main process is in dashed box, others are the optional strategies for each operation.

Figure 1 also lists 5 key steps in GA application and their corresponding optional strategies:

1) Initialization mainly involves parameter setting up, including population size, the maximum evolutional generation, probability of crossover and probability of mutation. However, how to set suitable values for these parameters are difficult in building a practical GA and there is no uniform standard [11].

2) Selection is a strategy for selecting individuals from the existing population to breed a new generation. There are numerous selection methods, such as roulette wheel selection, tournament selection, ranking selection, genitor selection, truncation selection and so on [11-13].

3) Crossover is a recombination operation that two selected “parents” are exchanged to produce two new “children” solutions.

4) Mutation is used for maintain genetic diversity by altering one or more gene values in a parent individual.

5) Termination is a major part for the determination of an appropriate point in time to terminate the search. There are three popular termination strategies: termination after a fixed number of generations, termination until solution meets the pre-set minimum requirement, or termination after reaching a plateau with no better results can be produced [14].

Those key steps as mentioned above will significantly affect the performance of GA. For example, a higher crossover rate may lead to premature convergence of GA, yet a higher mutation rate may result in the loss of good solutions. Therefore, it is worth to summarize the settings of GA in different applications.

3. GA IN BUILDING OPTIMIZATION

3.1 Applications in Building Energy Efficiency Optimization

In this review, we have identified 56 literatures from 1997-2014 related to building optimization by using GA. We find that the single objective optimization and multi-objective optimizations are almost account for half-half in the literature (Figure 2). About 40% of studies focused on building heating, ventilation and air-conditioning (HVAC) systems [15-19], about 45.7% were for building envelope [20-26], and 14.3% were for solar generation [27-29].

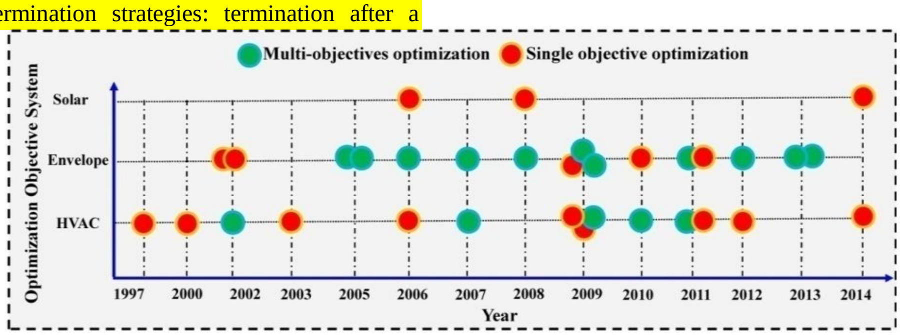

Figure 2. Research focus objects of GA application

Figure 3(a) shows that building optimization with GA in office and residential buildings constitute almost 78% of the applications. The remaining part is for school, business and hospital. Figure 3(b) illustrates that 68.4% of single-objective optimization employs the basic GA without any improvement, which is defined as GA with single-point crossover, bit mutation and maximum generation termination criteria. For multi-objective optimization, the basic GA method was extended including NSGA-II [30-34], MOGA [35-38], MIGA [39], RCGA [40] and ParetoGA [41].

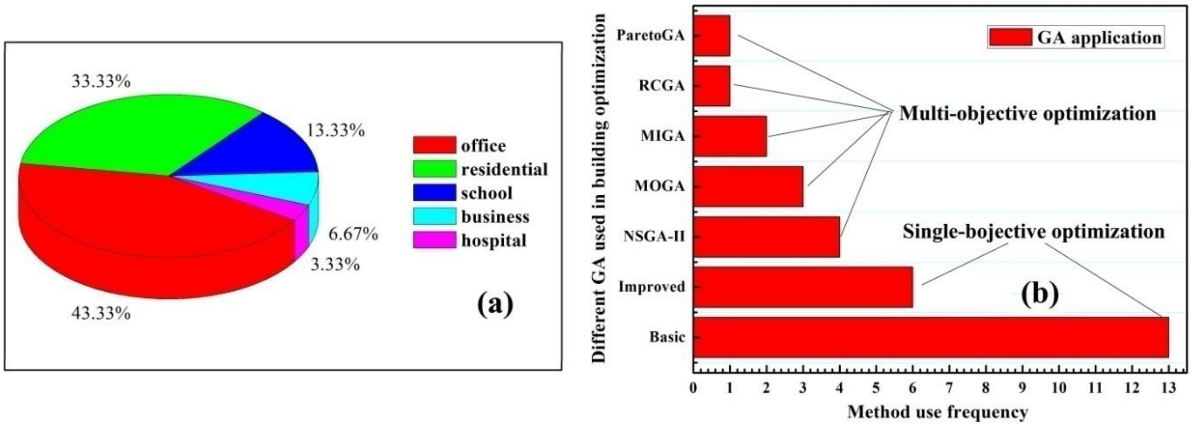

Figure 3. Summary of GA applications.(a)Trends of Building type.(b)Trends different GA improvement.

In addition, 26.5% and 17.6% of papers on GA optimization for buildings from this literature review is from USA and Canada, respectively. After that, China, French and UK each account for 8.8%. Papers from Japan and Serbia are about 5.9%. As for the simulation tools used in building energy optimization, TRNSYS, EnergyPlus and DOE2 are the top three simulation tools, whose proportion is about 25%, 21.4%, and 17.9%, respectively.

3.2 Settings of GA

As described previously, there are lots of GA related building optimization applications. At the same time, the parameter setting and operator selection will influence the convergence speed and population diversity of GA. Thus, these settings will determine if an optimal solution can be found. However, how to set up the parameters and select the operators depends on the problem nature. Therefore, to illustrate the application details of GA, we summarize all available information found from reviewed publications, as shown in Table 1. In which, Pc denotes the crossover rate and Pm represents the mutation rate. From 1997 to 2013, there are 17 references used GA to optimize the building.

Table 1. Parameters initialization of GA at different applications. "--"denotes that this information is not reported in the literature.

Author	Year	Parameters	Population size	Generation	P_c	P_m	Coding	Crossover	Selection	Mutation	Termination
Huang	1997	2	40	50	0.85	0.02	binary	two-point	--	--	maximum generation
Wang	2000	3	10	90	0.5	0.02	real	uniform	tournament	jump	maximum generation
Caldas	2002	8	5	100	1	0	binary	single-point	--	--	minimum criteria
Wright	2002	9	200	1000	--	--	binary	single-point	roulette wheel	bit	maximum generation
Wetter	2003	13	15	50	1	0.02	binary	single-point	proportional	bit	maximum generation
Wang	2005	10	40	300	0.9	0.01	binary	--	tournament	--	maximum generation
Wang	2005	10	40	200	0.9	0.02	binary	--	tournament	--	maximum generation
Wang	2006	17	40	300	0.9	0.07	binary	--	tournament	--	maximum generation
Lee	2007	4	40	10	0.8	0.1	binary	two-point	elitist ranking	bit	minimum criteria
Znouda	2007	12	200	1000	--	--	binary	--	elitism	immigration	same value during several iterations
Panão	2008	5	100	20	0.5	0.5	binary	single-point	random	bit	maximum generation
Palonen	2009	5	40	100	0.8	0.03	binary	single-point	tournament	bit	maximum generation
Ooka	2009	5	10	30	1	0.01	binary	two-point	elitist ranking	bit	minimum criteria
Pernodet	2009	8	200	3000	0.85	0.05	real	--	--	--	--

Magnier	2010	20	100	700	0.9	0.05	binary	simulated binary	mating	polyno mial	maximum generation
Evins	2012	21	100	200	0.7	0.5	binary	single-point	non-domination rank	bit	maximum generation
Gossard	2013	4	100	500	0.9	0.25	binary	simulated binary	random	bit	maximum generation

From Table 1, we can obtain the following conclusions:

1) For Coding method, binary coding accounts for 88.2%, yet the real coding accounts for 11.8%.

2) In terms of Selection methods, the most popular ones are tournament selection (35.7%) followed by ranking selection (28.6%).

3) For Crossover, the single-point crossover holds 50%, two-point crossover occupies 25%, simulated binary crossover is 16.7%, and the remaining 8.3% is uniform crossover.

4) For Mutation, the bit mutation is dominant which accounts for 72.7% of the applications.

5) For Termination, the ratio of maximum generation termination, minimum criteria termination and same value during several iterations termination are 75%, 18.75% and 6.25%, respectively.

Figure 4 reveals the relationship between the number of optimization parameters and the GA parameters.

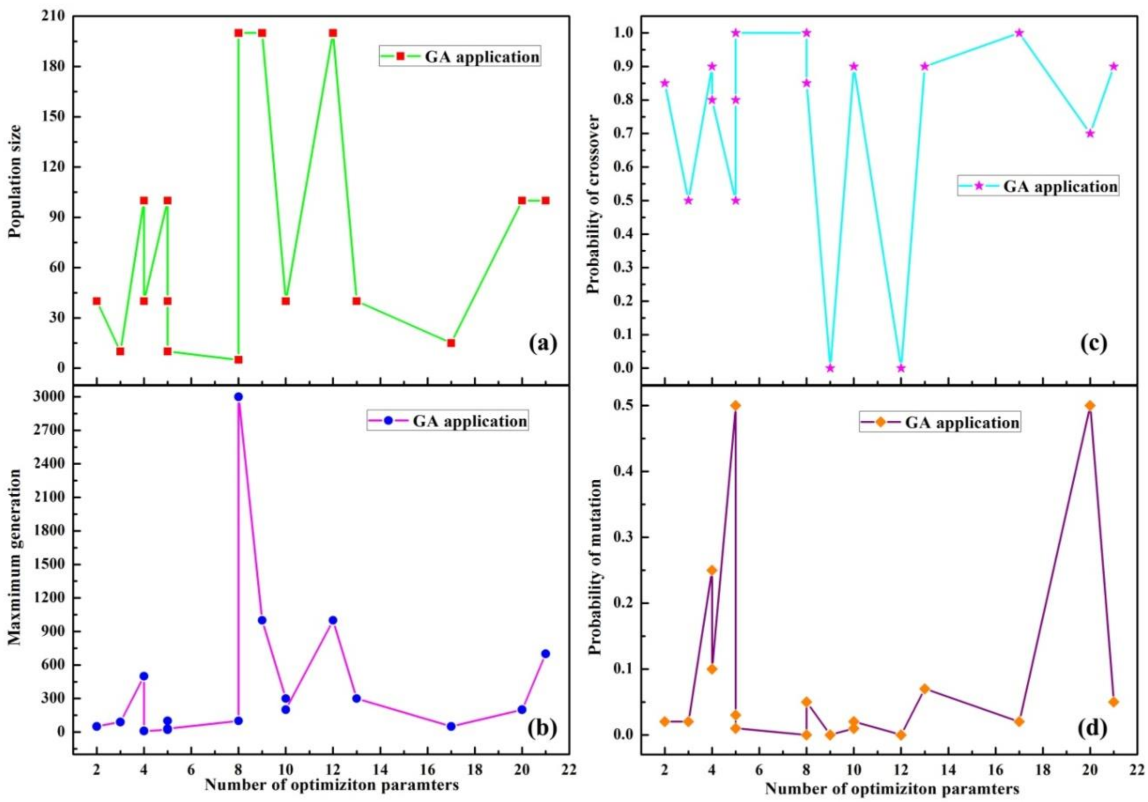

Figure 4. Summary of the GA parameters setting. The void parts of Table 1 are set for zero for plotting.

In terms of the population size setting up, 56.25% of reviewed applications are below 50, 25% is 100 and 12.5% is 200, as shown in Figure 4(a). Figure 4(b) shows that 75% of the maximum generation is set up to be lower than 300. From Figure 4(c) we can see that all of the crossover rate are set up between 0.5 and 1.0, and almost 85.7% of it are larger than 0.8. For the mutation rate, 73.3% of applications are smaller than 0.1 as shown in Figure 4(d). In general, the mutation rate is suggested to be smaller than 0.1 since a larger mutation rate will likely lose the optimal solution.

Based on the above analysis, we can give some suggestions on GA usage in Table 2.

Table 2. Suggestions on GA usage for building optimization

Parameter setting up	Condition
Population size<50	Optimization parameter number <16
Mutation rate<0.1	Optimization parameter number <21
Crossover rate>0.5	Optimization parameter number <21
Maximum generation<1000	Optimization parameter number <21

The program size and the searching speed of the GA strategy are the key factors affecting the practical application of the strategy. For example, a non-suitable operator selection can lead to poor performance of the GA in terms of both computation speed and reliability. Therefore, it is worth to study how to set up initial parameters and select operator for GA to improve its efficiency.

Especially, enhance GA's searching capability for real-time applications.

4. CONCLUSIONS

This paper focus on GA related building optimization application. Our literature survey shows that 90% of GA applications in building optimization are pure application without improving the basic GA algorithm. In addition, there are no general guidelines or theoretical support concerning the way of selecting a good selection method or crossover, mutation operator in GA for each problem. Therefore, research on GA parameter setting and operator selection method is significant for building energy optimization. Our future work will focus on the improvement of GA and discussion of its performance on building optimization for intelligent building operations.

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