Genetic Algorithms for Optimization of Building Envelopes and the Design and Control of HVAC Systems

Many design problems related to buildings involve minimizing capital and operating costs while providing acceptable service. Genetic algorithms (GAs) are an optimization method that has been applied to these problems. GAs are easily configured, an advantage that often compensates for a sacrifice in performance relative to optimization methods selected specifically for a given problem, and have been shown to give solutions where other methods cannot. This paper reviews the basics of GAs, emphasizing multi-objective optimization problems. It then presents several applications, including determining the size and placement of windows and the composition of building walls, the generation of building form, and the design and operation of HVAC systems. Future work is identified, notably between a GA and both simulation and CAD programs.

[DOI: 10.1115/1.1591803]
• Municipal utilities: dispatch of electricity generators, planning electricity transmission systems, scheduling of municipal water-supply pumps
• Robotics: design of multi-link mechanisms to follow a prescribed path, object recognition
• Signal processing: filter design
• Fault detection: detection of incipient sensor faults, design of fault-tolerant systems

Why Use a GA? GAs offer several attractive features:
• An easily understood approach that can be applied to a wide range of problems with little or no modification. Other approaches have required substantial alteration to be successfully used in building applications. For example, dynamic programming was applied to the problem of selecting the number, location, and power of lamps along a hallway to minimize the electrical power needed to produce the required illuminance [4]. Because the choice of the location and power of a lamp affected decisions made about previous lamps, the sequential decision-making approach inherent in dynamic programming could not be made. It was necessary to suspend earlier decisions and reconsider them, substantially increasing computation time and data storage.
• Publicly available, easily implemented GA codes. Reduced set-up time makes them attractive relative to other optimization methods that may offer better performance but must be identified, obtained and properly configured.
• Inherent capability to work with complex simulation programs. Simulation does not need to be simplified to accommodate optimization.
• Proven effectiveness in solving complex problems that cannot be readily solved with other optimization methods. The mapping of the objective function for a daylighting-design problem showed the existence of local minima that would potentially trap a gradient-based method [5]. Building optimization problems may include a mixture of a large number of integer and continuous variables, non-linear inequality and equality constraints, a discontinuous objective function and variables embedded in constraints but not in the objective function. Such characteristics make gradient-based optimization methods inappropriate and restrict the applicability of direct-search methods [6]. The calculation time of mixed-integer programming (MIP), which was used to optimize the operation of a district heating and cooling plant, increases exponentially with the number of integer variables. It was shown to take about two times longer than a GA for a 14-hr optimization window and 12 times longer for a 24-hr period [7], although the time required by MIP was sufficiently fast for a relatively simple plant to make on-line use feasible.
• Methods to permit GAs to handle constraints that would make some solutions unattractive or entirely infeasible.
• Identification of optimal trade-offs among multiple optimization criteria, a topic to be discussed next.

Multi-Objective Optimization

Single-objective optimization may unnecessarily constrain a designer. For example, operating costs for lights and for space conditioning can both be expressed in the same units, but a designer may have reason to favor daylighting from north-facing windows over increased conduction losses and attendant increases in heating and cooling costs. Capital costs for equipment and the building envelope can in principle be included in a life-cycle-cost objective function but may better be considered separately, if capital and operating budgets are separate. Multi-criteria optimization methods move away from a sum (weighted or unweighted) of individual objectives and provide the designer with explicit information about the trade-offs between different criteria.

There are several approaches to multiobjective optimization problems using GAs:

• Simple aggregation or weighting of individual objectives;
• Population-based non-Pareto approaches;
• Pareto-based approaches.

Simple Aggregation. Individual objective functions can be combined by using weighting factors based on some knowledge of the problem, forming a single figure of merit that reflects the overall performance of the solution according to the different objectives. Then GAs can be applied repetitively, if necessary, changing the values of the weighting factors at each run, to gain some insight into the relative importance of each of the objectives.

Population-Based Non-Pareto Approaches. These approaches seek to discover multiple non-dominated solutions, but without explicit use of Pareto fitness. The Vector Evaluated GA (VEGA) [8] selects sub-populations of the next generation according to individual objectives. Overall fitness is a linear combination of individual objectives, with weights that depend on population distributions. Fourman [9] selected a new population by comparing pairs of individuals, each according to one of the objectives.

Pareto-Based Approaches. Pareto optimality makes use of the concept of dominated and non-dominated solutions. A solution is Pareto optimal if it is not dominated by any other solution. In Fig. 1, the points represent feasible solutions to a multi-objective maximization problem, where values for each of two objective functions are assigned to the x and y axes. A solution dominates another if it is better than the other for at least one objective function and at least as good on all the others [10]. Point A (4,2) dominates point C (3,1) because it has both higher x and y values. Points A (4,2) and B (2,4) are not dominated and are therefore both Pareto-optimal solutions. They represent good trade-offs between the two objective functions. Point A performs better than B in terms of the x values but the inverse is true for y values.

There are several Pareto approaches to evolving a population that optimizes the trade-offs among objective functions:

• Pareto optimality of an individual, with the same ranking assigned to all non-dominated individuals [11] or with a ranking assigned to equal the number of individuals by which it is dominated [11].
• Tournament selection [12]. The best of a randomly chosen subset of individuals is chosen for the next generation.
• Pareto reservation strategy [13]. All non-dominated individuals in a population are retained. If necessary to fill out the population of the next generation, remaining individuals are selected via a VEGA.
The literature reports that GAs have been well suited for generating a Pareto front because they offer many of the advantages of GAs but typically work with a single solution and single objective function, has also been used for multi-objective problems, by archiving nondominated solutions. Simulated annealing, an optimization technique, is used to spread the population of Pareto-optimal solutions over the entire Pareto front. Crowding and fitness sharing have been used to maintain genetic diversity.

GAs are well suited for generating a Pareto front because they work with a population of solutions. Simulated annealing, an optimization that offers many of the advantages of GAs but typically works with a single solution and single objective function, has also been used for multi-objective problems, by archiving nondominated solutions.

### Optimization of the Building Envelope

**Previous Work.** The literature reports that GAs have been used to manipulate building form and wall construction, to present individuals in a population are retained and all dominated individuals are discarded.

- Non-dominated Sorting Genetic Algorithm (NSGA) [14]. Niche-induction techniques are used to spread the population of Pareto-optimal solutions over the entire Pareto front. Crowding and fitness sharing have been used to maintain genetic diversity.

- Pareto-optimal selection method [10]. All non-dominated individuals in a population are retained and all dominated individuals are discarded.

- NSGA [14]. The GA controlled the DOE-2 building-energy simulation program [21] to manipulate window size and placement as a means of minimizing a single objective function—energy consumption.

- DOE2 code 2003

**Optimization of Building Materials.** In a second phase of work by the authors, not previously reported and described here in detail, optimal trade-offs between reductions in energy consumption during building operation and initial costs due to construction materials were evaluated [22]. Two sets of experiments were performed. The first made use of a five-zone office building with weather data from Phoenix and Chicago, and the second focused on an apartment in Beijing, China.

The office building featured independent rooms facing each cardinal direction, one window per room (in the longest exterior wall), and a small core. Figure 2 shows the building layout. All walls were constructed in a similar fashion. The interior finish was gypsum board and the outside layer was a 2.5-cm stucco layer. The search algorithm manipulated materials for three internal layers. Material 1 represented the material used for the layer closest to the external wall surface, material 2 was the middle layer, and material 3 was the layer closest to the inside surface. The GA was allowed to choose from a list of 16 possible materials, shown in Table 1. Materials and their physical properties were selected from the DOE-2 materials library. A constraint prevented materials 1 and 3 from being air layers, due to buildability issues. The glass, fixed for all the experiments, was double-layer clear glazing (DOE2 code 2003), with a shading coefficient of 0.81, a visible transmittance of 0.78, and a U value of 3.16 W/m$^2$ K.

Costs for the different materials were obtained by averaging prices provided by several retailers in the U.S. If quantity discounts exist, they could be handled by if-then type of rules, of the kind "if material x area is greater than y, then cost of material x equals z, else if ..." In general, costs per unit area of insulation materials were lower than those for concrete block. Expanded polystyrene was more expensive than expanded polyurethane. Air layer costs were set to zero. Window costs were much higher per unit area than any of the other materials.

Experiments were done for Phoenix and Chicago climates. Figure 3 shows the progression of the search for the Pareto front for the Phoenix climate, from the initial random population of generation 1 to generation 100, where the Pareto front is clearly visible. Running another 100 generations made small improvements in the front, but also removed some previously found points. Although not shown, most of the front was defined by generation 20, with subsequent generations making small improvement.

Numerical information is provided in Table 2. In general, larger window sizes, particularly towards the south and north, led to better performance solutions but at higher capital cost. There was a strong correlation between smaller windows and increased energy consumption. The west façade seemed to be an exception: even in the best solutions the window sizes were rather small. East windows were somewhat larger.

Even though many instances of heavyweight, masonry elements appeared in the first, random solutions, only lightweight, insulation materials were used in the final Pareto solutions. Recall from Table 1 that material numbers 1–3 are air layers, 4–8 are insulation materials, and 9–16 are different types of concrete blocks, some filled with perlite. Looking at Table 2, it is possible to see that all material numbers are smaller or equal to eight, meaning that only insulation materials and air layers were applied. The cost per unit area of insulation materials was lower and the GA may

![Fig. 2  Schematic building layout for Pareto experiments](image-url)
have used the thermal mass from the concrete floors and roofs as heat storage during the day to avoid large peak loads. It was expected that in a hot climate like Phoenix some thermal mass would be applied in the walls. However, the massive floors and ceilings seemed to be able to take that role, allowing the walls to become lightweight, highly insulated elements. Finally, it was possible to see that the lowest energy solutions make use of better insulation materials, like #6 (7.6 cm expanded polystyrene, the thickest allowed), and #8 (5 cm expanded polyurethane, also the thickest). To reduce construction costs to the detriment of energy consumption, the GA used large air layers and lower quality insulation materials, combining that with a reduction in window sizes.

One of the randomly generated solutions in the first generation performed almost as well as the best Pareto solution in terms of energy, but its construction costs were about 33% higher. This demonstrates the usefulness of applying the Pareto-front search. The reduction in annual energy consumption from the first to the hundredth generation was only 6% on average from 24.7 MWh to 23 MWh, but the reduction in construction costs was about 41% from $8434 to $4965, suggesting that including materials...
costs in the Pareto-front studies may be an effective measure for achieving similar energy performance at lower first costs.

The second set of experiments related to a simple test box, \(10 \times 7 \times 3\) m, that was used to represent a hypothetical apartment in Beijing. The shorter sides of the apartment were exposed to the exterior, and faced south and north. The other walls, floor and ceiling were modeled as adiabatic surfaces, assuming the apartment was part of a larger building.

This problem introduced as variables the solar absorptivity for exterior walls and different glazing types. The construction materials for south- and north-facing walls were also allowed to be different, because it was hypothesized that south-facing walls would give the same energy performance with less insulation, due to absorbed solar energy. The two objective functions used were annual energy consumption and materials costs, including windows. Materials used for this study were those presented in Table 1. Wall absorptivity was varied between 0.2 and 0.8, in 0.2 steps. The two glazing options were a single layer of clear 3-mm thick glass, with a shading coefficient of 1, visible transmittance of 0.898, and a U-value of 6.31 W/m² K, and a 12-mm gap, a shading coefficient of 0.89, visible transmittance of 0.812 and a U-value of 2.79 W/m² K.

Figure 4 shows the first initial random generation and the final Pareto front for tests with the exterior walls facing south and north. Solutions in the first generation used many types of wall and glazing materials and many values for window dimensions and wall absorptivity. The average annual energy consumption of the random population was 6.5 MWh, and the average cost was about $3500. In contrast, the Pareto solutions for the final generation showed a much greater convergence of variable values. All windows were double-glazed. North-window dimensions were in general very small. South-window dimensions were of average size for the best energy-performance solutions but significantly smaller than the maximum allowed by constraints. Decreasing south-window size was the best strategy to reduce construction costs but had detrimental effects on daylighting and useful solar gains, and led to increased energy consumption. The south-wall absorptivity was always at high values, either 0.6 or 0.8. The north-window absorptivity had more random values, because solar gains were not significant in that direction.

The south-facing large spaces easily penetrated by daylight. The south-facing large spaces were of average size for the best energy-performance solutions but significantly smaller than the maximum allowed by constraints. Decreasing south-window size was the best strategy to reduce construction costs but had detrimental effects on daylighting and useful solar gains, and led to increased energy consumption. The south-wall absorptivity was always at high values, either 0.6 or 0.8. The north-window absorptivity had more random values, because solar gains were not significant in that direction.

The north walls were essentially filled with insulation. Insulation was used in the outer layer of the south walls but inner layers tended to be air spaces in the more cost-saving solutions, with a subsequent decrease in energy performance. In order to save costs, poor insulation materials were used in the south wall, together with the introduction of air layers, but the north wall remained highly insulated for most cases, only decreasing towards the worst performance solutions.

The average energy consumption level of the population decreased by 33% in relation to the initial random population, while the costs were reduced by 68%, a very significant value. Masonry use was completely excluded, because insulation materials were less expensive and the floor slabs provided some amount of thermal mass.

Another set of experiments was done with the building rotated by 90 deg, so that it would face east-west instead. Energy-consumption levels were always higher for this orientation than for S\(\rightarrow\)N, as expected. However, costs remained lower, because the sizes of the relatively expensive windows were very small, even in the best energy-performance cases.

**Optimization of Building Form.** In a third phase of work by the authors, GAs were employed to alter building form to optimize the trade-off of lighting and heating energy [22]. The starting point for this study was a two-story structure with four equal-area square zones on each floor. The GA manipulated the size and shape of each zone and could tilt the roofs of each zone. A penalty was applied to the objective function to inhibit the GA from unduly reducing the size of the zones. Figure 5 shows points along the Pareto front with associated building forms and Fig. 6 shows the forms in more detail.

The best solution for heating energy is a single, compact, large space facing northeast, with thin, sunspace-like, all-glazed south and west elements surrounding it. This happens both in the first and second floors. The best solution for lighting is formed by small spaces easily penetrated by daylight. The south-facing large glazing areas still exist in this solution, in long and thin rooms facing south. The intermediate solutions show the transformation from one end-point solution to the other. Solutions 4 and 5 are interesting, showing very long and thin south-facing elements and a number of smaller, north-facing spaces.

**HVAC Design and Operation**

**Previous Work.** A GA was employed to optimize design variables in an HVAC system [23], including the physical dimensions of the system components (discrete), the operating point of
the system as represented by the controller set points, and such parameters as the maximum mass flow rates (continuous). The design constraints covered the upper limit of the fluid velocities, the control range of the fin-tube coils, the water circuit configuration of the coils, the maximum supply-air-to-room-air temperature difference, and failure of the simulation due to undersizing or oversizing of one or more components. The objective function was the capital cost of the system.

The work of [23] was extended to include simultaneous optimization of the HVAC system size, the HVAC-plant-control strategy, and the building-envelope construction [6]. The objective function was selected to be energy cost. Variables for system size included supply-fan size and coil width and height, number of rows and water circuits, and water flow rate for both heating and cooling coils. Operation variables included equipment on-off status during unoccupied hours, mass flow rate of supply air, and supply-air temperature. Building construction was characterized by building weight and glazing type and area. All variables were constrained within upper and lower bounds.

Additional design constraints placed limits on the predicted percentage of dissatisfied (PPD) occupants, the air face velocity through the coils, and water velocity, and fan speed and volume flow rate, to ensure compliance with manufacturer’s data. A normalized sum of constraint violations was developed as a measure of the infeasibility of solutions, a method more effective in a highly constrained problem than the so-called death penalty that eliminates without further consideration all infeasible solutions.

Trade-offs between operating costs and thermal comfort and between operating and capital costs were explored for the same system, with multi-criteria optimization and GAs [24,25]. The Multi-Objective GA [26,27] used in the project treated constraints as criteria and penalized the Pareto rank of infeasible solutions. Constraints were normalized and aggregated to form a single constraint criterion. This approach restricted the increase in dimensions of the Pareto front and made it possible to easily remove the constraints from the search when feasible solutions were found.

HVAC duct layout was designed with a GA [28]. Unlike existing approaches, the GA was able to account for discrete duct sizes, variations over time in operating conditions, and variable electricity pricing.

The control parameters for a heating coil were optimized with a GA [29]. The system featured a boiler, heating coil, and primary and secondary pumps. The secondary pump maintained a constant flow through the heating coil. A three-way valve regulated the mix of hot water from the boiler and recirculated water from the heating coil, to vary the temperature of the water through the heating coil as a means of regulating the discharge air temperature. The GA was used to select the proportional and integral gains of the valve controller, in order to minimize an objective function that was a weighted sum of overshoot, settling time and mean squared error associated with a step change in the discharge-air set point. The GA was coupled with HVACSIM+ [30–33], which was used to perform a detailed simulation of the system for each control-parameter configuration. The GA identified control parameters that gave a smaller overshoot and settling time than the Ziegler-Nichols method [34]. Implementation of this approach as an on-line adaptive controller was not discussed but would require identification of the parameters in the system model. Other methods have been developed for improved tuning of HVAC control loops, notably an adaptive controller that makes use of observed patterns in controller response to set point changes and disturbances and selects gains on the basis of off-line simulations [35].

A GA was used for both parameter identification and control optimization in a simulated heating system and single-zone building [36]. The system was modeled as an RC network, using bond graphs to establish the typology, and was simulated with a general-purpose equation solver. First, the model of the system was used to produce a time history of room and storage-system temperatures as a function of heat inputs directly to the room and to the storage system. The thermal resistance and thermal capacitance of the heat storage system were then removed from the model and the GA was used to adjust values for the two parameters to match the room and storage-system temperatures. Parameters that described the thermal properties of the outside wall were not masked from the GA. For schedule optimization, the GA was combined with a hill-climbing procedure to reduce the search space and therefore improve the efficiency of the GA. The schedules of the direct and storage heating systems were optimized to provide at minimal cost an indoor temperature above a specified minimum.

Load Control. A GA was used by one of the authors of this paper to schedule reductions in lighting and cooling power during a load-control period [37]. Building response to load control over

Fig. 5 Pareto front points for generation of building form. Two views are shown for each solution, from the southwest and northeast.
a single day was simulated with a two-resistor two-capacitor model of a single room, based on a popular general-purpose engineering mathematics program [38]; the publicly available GA was coded in the same simulation environment. The objective function always included energy consumption and optionally included peak power and temperature deviation from set point.

Two sets of simulations were done for a single building: a GA search and an exhaustive search. First, the GA was used to find the optimal solution, for different forms of the objective function. Members of the population were defined by the limit on air conditioning, the hour in which that limit would take place, and a similar limit and hour for lighting. For purposes of the GA, the step size for limits on air conditioning and lighting was defined as 0.1, ranging from 0 (no service) to 1.0 (no reduction in service).

Fig. 6 Pareto front points. Solution 1 represents the best building shape in terms of heating. Solution 6 is the best building shape in terms of lighting. The other images represent intermediate solutions.
The load-control period was 4 hr, noon–4 p.m. The GA search was performed for the four possible combinations of population size, 3 and 10, and number of generations, 2 and 10. In each case, the GA was set up to remember all past simulations and not repeat a simulation in its search for the optimum.

The GA results were compared with the optimal solution found by an exhaustive search. The exhaustive search was limited to control steps of 0.2. With this step size and a four-hour load-control period, the number of possible load-control actions was 576 (6 load-control steps over 4 hr for air conditioning and for lighting). Table 3 compares the results of the GA and exhaustive searches and shows that the GA successfully found near-optimal solutions for each set of objective-function weights. The following observations were made:

- The peak air-conditioning load increased when air conditioning was curtailed, due to the pick-up load in the hour following the reduction in cooling. With a demand charge, the increase in load led to an increase in the objective function.
- While many combinations of lighting and air-conditioning curtailment produced similarly low values of the objective function (weighted cost of energy and loss of service), others were poor choices with objective functions that were 15% higher than the best choices. High objective function values were associated with reductions in air conditioning that saved little energy and greatly increased the thermal-comfort penalty.
- While the GA was able to find relatively small differences in objective function, it did not consistently find the absolute minimum when the search space had a shallow contour. However, the extent of suboptimality was trivially small.
- Because the problem had a large number of near-optimal solutions, the GA search could be limited to small populations and a small number of generations.
- The same control strategy produced the best performance for all six sets of weights on demand, energy, and thermal performance: turning off the lights completely for one hour, which was not subject to a visual-comfort penalty, and limiting the air conditioning output to 0.6 of maximum value for a single hour. A second strategy produced the worst performance: turning off the air conditioner for an hour and maintaining the lights at rated power throughout the load-control period. This suggested that some amount of off-line testing could establish heuristics to supplement or replace time-critical on-line simulations.

Table 3: GA and exhaustive searches for optimal control schedule, as a function of population size, number of generations, and weighting function. The weighting function now includes a weight on electricity demand.

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Conclusions

GAs have been successfully applied to a number of problems concerning building energy use and HVAC systems. They can readily handle large problems, such as simultaneous optimization of the building envelope and the design and operation of an HVAC system, and duct design to minimize first and operating costs over a range of operating conditions and electricity prices. Because they work with a population of solutions, they naturally provide optimal trade-offs among multiple design criteria. Multiple solutions are of particular value when building form or window size and placement are optimization variables, because typically there are many other design criteria to consider, not included in an optimization.

A number of large-scale optimization problems may be appropriate for GAs: siting of buildings to optimize the use of wind-driven ventilation and daylight, optimal control of HVAC equipment in an aggregate of buildings to minimize electrical power during peak-demand periods, and more work on the generation of building form.

GAs will be more widely used when there are publicly available and easy-to-use interfaces with energy-simulation codes. While GAs can and have been used with such codes, it has been necessary to develop a custom interface, to convert the GA's specified value for a given variable to an appropriate input value in the simulation code. An interface is also required to obtain output from the simulation package and form the objective function. Last, the use of GAs to generate building form or building facades would benefit from an interface that would allow designers to generate initial solutions in a CAD program and view the GA-modified solutions in the same CAD environment.

Acknowledgments

L.G. Caldas acknowledges financial support from the several institutions: the Fundação para a Ciência e a Tecnologia, Praxis
XXI program, Portugal; the Fundação Cultural Luso-Americana, the Fulbright program; the V. Kahn-Rassmussen Foundation; and MIT, through a Rosenblith Fellowship. L.K. Norford acknowledges the financial and technical support of ASHRAE, via research project 1120-RP.

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