EVOLUTIONARY ALGORITHM WITH THREE DIFFERENT PERMUTATION OPTIONS USED FOR PRELIMINARY HVAC SYSTEM DESIGN

Magdalena Stanescu¹, Stanislaw Kajl¹, and Louis Lamarche¹
¹ École de technologie supérieure, Montréal (Qc) H3C 1K3, Canada

ABSTRACT
This paper discusses an HVAC system design optimization using a detailed simulation method as well as an evolutionary algorithm using three different permutation options. The detailed simulation method was used to evaluate the objective function, i.e., HVAC energy consumption, calculated using DOE-2 software. The variables for the optimization problem were: (i) grouping of the zones served by the systems and (ii) number of systems serving each building. Constraints were selected in such a way that the limits of the variables were well represented. A comparison of the optimization results, computing time as well as convergence speed was carried out in order to select an optimal solution.

INTRODUCTION
HVAC (heating, ventilation and air conditioning) systems are recognized as the greatest energy consumers in commercial and institutional buildings. Generally, designers use common sense, historical data, and subjective experience in designing these systems; this includes the number of systems chosen and the grouping of the zones served by these systems. HVAC energy efficiency is not an easily calculable criterion during the selection of these systems; usually the first selection criterion is the weakest investment cost.

For this article, we used a real institutional building, that is to say the B-Pavilion at École de technologie supérieure (ÉTS) in Montréal, built in 2004. We modelled the building using the DOE-2 calculation engine (commercial software developed by the United States Department of Energy, LBNL 2003). We used the building’s own grouping of zones by system as well as the number of systems in this building, as designed by its mechanical engineer, to define the existing building.

This article briefly describes the method used for creating an HVAC optimization design for this building, already described by Stanescu et al. (2011). The B-Pavilion, with its existing systems, is shown in Figure 1. Analyzing the energy bills for this building, we found that the existing HVAC system design was already a good one. To highlight the impact of optimization on energy consumption, we also created a reference building with its own system design: one system per façade (i.e., 4 VAV systems); a system serving a few zones located at Levels 3 and 4 on the east side of the building (System UTA-7 in the existing building), and another system covering the internal zones. This kind of reference building was used in our previous work as a comparison tool because of its less efficient design. The existing building and reference building were used as comparison tools for our optimization methods.

We then describe the results of our optimizations, which included grouping of zones and number of HVAC systems for the building. Evolutionary algorithms (EAs) with three different permutation options and having HVAC energy consumption as the objective function were used for optimization. The three approaches used for optimization were: an EA using crossover and mutation as variation operators; an EA using only crossover as variation operator, and an EA using only mutation as variation operator. Optimization results, computing time and convergence speed were compared in order to select an optimum solution for our problem.

The results of the optimization approaches propose design choices including grouping of zones and number of HVAC systems for the building that could prove quite interesting for engineers during the preliminary design phase. While type of system was preselected for this study, it could be serve as an optimization variable. Comparing the (i) existing, (ii) reference and (iii) optimized buildings (all having the same constraints) yielded significant savings in HVAC energy consumption. These savings generally depended upon several factors: the building’s configuration; the types of HVAC systems employed and their control strategies, and the constraints imposed.

GENERAL DESCRIPTION
Building description
The building studied is a university institution housing an 11.5-month teaching program. Built in 2004, it is located in Montreal. The footprint of this building is 4639 m² and the building is 34.11 m high. The entire simulated surface is 28,598 m² (31,388 m² of rough surface) and this area is set out over an underground parking zone as well as over five floors. The main zone categories for this building are:
classrooms (4691.5 m²), laboratories (402.1 m²), offices (3825 m²), corridors and supply rooms (5695.6 m²), cafeteria (457 m²), kitchen (457 m²), gymnasium and training room (2011 m²), locker-rooms (355 m²), toilets (388.6m²), and a parking zone (9834 m²).

The building’s characteristics are as follows:

- principal orientation North (azimuth of 40°)
- average window to wall ratio of: 23% North, 38% East, 31% South, 32% West
- RSI = 3.5 m²C/W for external walls; RSI = 3.1 m²C/W for the roof
- double clearly powerful Low-E window with argon space (U=1.32W/m²C, Shading Coefficient of 28); the glazing is fixed without frame

HVAC system description

There are seven (7) HVAC systems installed in the existing building, including:

- 4 VAV (variable air volume) systems serving each of the following zones: classrooms, offices, corridors, workout room and small cafeterias. Zone grouping is shown in Figure 1, except for system UTA-107, which supplies mainly the training room located on the east side of the building; this system is not mentioned in Figure 1.
- Two CAV (constant air volume) systems, serving both gymnasiums as well as the mechanical room at Level 4 (Systems UTA-105 and UTA-106). The vocations of zones served by the systems using constant air flow rates (CAV or make-up systems) were so specific that these zones were excluded from our optimization.
- One make-up system (UTA-101), providing 100% of the outside air for the nursery and the pub.

Each HVAC system is provided with CO₂ sensor detection. Minimum weekday operating schedules are from 6 a.m. to 11 p.m. (17 hours per day).

As mentioned above, a reference building was simulated and used as a comparison tool in this study. This reference building was provided with six (6) VAV systems: one for each facade (i.e. 4 VAV systems); one VAV system mainly for the training room on the east side of the building, and one VAV system for the building’s internal zones.

The grouping of zones by main systems for the reference building is shown in Figure 2.

Thermal plant

The thermal plant has one chiller that provides chilled water for space cooling, using the cooling tower located on the roof. The centrifugal chiller has a cooling capacity of 450 tons (1582.5 kW) and uses R-134a as refrigerant. Superheated steam from the Montreal Community Steam Power Plant (CCUM) is used for space heating and for service water heating. Rooms with specific demands, such as the server/telecom rooms or computer rooms are served by individual heat pumps which are cooled by a second cooling tower.

OPTIMIZATION

As described by Stanescu et al. (2011) in previous work, we had optimized the building’s system design in order to carry out a better grouping of the building zones served by its systems. In our article we described the modifications required by the optimization procedure (CR_CONS) at the beginning of the design process, as suggested by ASHRAE (1993). Figure 3 provides a reminder of this modified design process, including the optimization procedure we used.
Evolutionary algorithm optimization

Evolutionary algorithms using single objectives were therefore used in the method we are proposing for optimizing HVAC system design.

Figure 4 shows an optimization using EA, including an interaction with DOE-2 software when calculating the objective function, that is to say, HVAC system energy consumption.

Steps 1 and 3 employed DOE-2 software for modeling and simulation. Interactions between DOE-2 and the EA are shown in the section entitled “Simulation of the building.” Step 2 occurred just once at the beginning of optimization, and represented the initialization of the first population of individuals that would need to evolve. For this reason, in this section we will discuss only EA operation in the optimization process.

In order to define our specific EA, we must describe a number of components, procedures and operators, such as: representation of individuals, evaluation function, population, parent selection mechanism, variation operators and a survivor selection mechanism.

The first stage in creating an evolutionary algorithm is to decide on a genetic representation of a candidate solution, which was, in our case, a permutation representation of a set of integers. The length of our permutation vector represented the number of zones in the building, each of which occurs exactly once. The zones were placed randomly in the vector, and in order to group zones into systems we used randomly selected break points. Increasing the number of break points by one guided us towards finding the number of systems. For example, the first system was represented by the zones placed at the beginning of the vector up to the first break point; therefore, the order in which elements occur is important.

In order to represent valid permutations, variation operators were needed, to preserve the permutation property of each possible allele value occurring exactly once in the solution.

We chose the tournament selection operator to select parents, because of its simplicity and because selection pressure is easy to control by varying tournament size. Tournament selection involves running several "tournaments" among a few individuals chosen at random from the population. Selection quality can be adjusted easily by changing tournament size (n): if a tournament size is greater, then there are more chances that it will contain members of above-average fitness; and if a tournament size is smaller, then it is likely to contain low-fitness members. In our case, there were as many tournaments as there were individuals to select. The winner of each tournament (the one with the best fitness) was selected for modification. To keep from losing the best solution found, we used elitism, placing the individual with the best fitness into the next generation, thereby increasing EA performance.

We then applied variations operators in order to maintain diversity within the population and inhibit premature convergence.

Three forms of mutation were chosen: swap mutation, insert mutation and inversion mutation. Swap mutation works by randomly picking two positions in the string and swapping their allele values. Insert mutation works by picking two alleles at random and moving one so that it is next to the
other, shuffling along the others to make room. Inversion mutation works by randomly selecting two positions in the string and reversing the order in which the values appear between those positions (Eiben and Smith, 2003). The probability of mutation can be applied at two levels: the chromosome level and the gene level (Wright et al., 2004). The probability of gene mutation varies according to the form of mutation operator use. The three operators below work by making changes to the grouping of zones by system, and by keeping the same number of systems. To maintain diversity in the population, we also wanted to modify the number of systems. For this reason, we chose a break point randomly.

The crossover form we employed is called order crossover. Order crossover begins by copying a randomly chosen segment of the first parent into the offspring. From the replaced portion on, the rest is filled up by the remaining genes in the order in which they appear in the second parent, where genes already present are omitted and the order is preserved (Eiben and Smith, 2003).

The main genetic operators for our optimization problem were therefore: selection (tournaments); mutation (inversion, sliding, insertion and change in number of systems-nbs); and crossover, depending on the type of EA we chose to employ. A new, improved population was then created. The counter was increased to indicate that a new generation had been completed (Deb, 2001).

Identification of the objective function, variables and constraints

A design optimization problem can be characterized using the problem's variables, objective function and constraints.

The objective functions generally used in HVAC system design are the criteria used by design engineers for comparing candidates' design solutions; these objective functions (i.e.: system-operating cost, capital cost, life-cycle cost) are usually nonlinear (Fong et al. 2006, Wright and Hanby 1987, Hanby and Wright 1989). Our problem's objective function was energy consumption by HVAC systems, computed using DOE-2 software for each individual in the population generated by the evolutionary algorithm. Our objective was to minimize the objective function. Thereafter, individuals with the lowest energy consumption from each tournament were selected and modified in order to create the next population.

The variables for an optimization problem when designing HVAC systems are: (i) grouping of zones served by systems and (ii) number of systems serving a building. For this study, system type had already been chosen (VAV system type), but it could also have served as a variable.

Although this problem appears straightforward, it is actually quite complex, because the two variables previously mentioned are dependent: if the number of systems changes, then the grouping of the zones changes as well. The danger exists of finding the same zone several times within the same grouping. As mentioned above, in order to bypass this problem, we used permutation representations for individuals.

In general, constraints represent the higher and lower limits of problem variables, either directly or indirectly. It follows that, in order to avoid the risk of having system airflow rates that were too low or too high, system size became our first constraint, and was represented by minimal and maximal airflow rates (AFR). We accomplished this by limiting the system's minimum and maximum design AFR to 8% and 50% of total AFR (calculated using the building's corresponding peak load), respectively. This constraint indirectly gave us the minimum or maximum number of systems allowed during optimization, i.e. between 2 and 12 possible systems.

Our second constraint was the size of the system's air ductwork, which took into account the location of zones served by the same system in order to reduce costs associated with the air duct network. The design of air ducts for VAV systems has already been the focus of an optimization method developed by Kim et al. (2002) using GA. In our case, this problem was quite complex due to the large number of parameters involved, which changed for each EA-generated individual. For this reason, we developed a simplified and indirect method for taking into account the size of system air ductwork: we considered that the distance between the centre of gravity of all zones served by a single system and the mechanical room could serve as a good approximation for quantifying the size of system air ductwork. We applied a weighting method to each segment using airflow rates, and to characterize this weighted size we named it "system extent" and coined a term for the unit: \([m_{\text{extent}}]\). (Stanescu et al., 2011)

SIMULATION OF THE BUILDING

Optimization using a building energy simulation program is often used to reduce annual heating and cooling energy consumption, even though this requires a significant amount of experience, time, and effort to enter detailed building parameters (Bambrook et al. 2011, Smith et al. 2011).

Our optimization method required the detailed building model in DOE-2 software to determine HVAC energy consumption as shown in Figure 5. All the data shown below, as well as the architecture, electricity and ventilation plans, were necessary in order to design the building model. Once we had defined the building in the simulation software, along with its architecture, envelope components, vocation, lighting and zone equipment, we proceeded to define its HVAC systems and plants. Because the vocation of thermal zones would remain unchanged during the optimization process, zone load was calculated once,
at the beginning of the process (Figure 4, Step 1). The ‘typical year’ weather input used in our building energy simulation was the one for the City of Montreal (CTMY2 file). The EA began by initializing the first population of individuals needing to evolve. (Figure 4, Step 2). Modelling of the building had to be completed for each individual, and depended upon the variables selected by the EA (number of systems, and grouping of the zones). This action was carried out for each iteration (Figure 4, Step 3). Definition of HVAC systems depends upon choice of variables; these were chosen both at the beginning of the optimization process (Figure 4, Step 2) and during the EA optimization process (Figure 4, Step 3). These variables influenced some system parameters, such as design airflow rate, fan power, system operating schedule, and temperature difference across fans. HVAC systems were defined for each individual generated (Figure 4, Step 3), taking into account the zone loads already calculated in Step 1.

To calculate fan power, we used ASHRAE 90.1 standard correlations (ASHRAE 2004): for an airflow rate less than 20,000 cfm (9438.9 L/s), fan power was 1.7 hp/1000 cfm (1.26 kW per 471.9 L/s), and for an airflow rate greater than 20,000 cfm (9438.9 L/s), fan power was 1.5 hp/1000 cfm (1.11 kW per 471.9 L/s). Each system's operation schedule was viewed as the union of all operating schedules for the zones served by that system.

The temperature difference across fans was calculated based on fan efficiency (70% in our case) and on the efficiency of the fan motor. We adjusted the parameters for each individual and for the size of the building's plant equipment. Using DOE-2 software, we obtained HVAC system energy consumption for each individual in the EA population; this gave us a selection criterion for defining the next population.

Legend:

![Figure 5 Building zones for the five levels of the B-Pavilion at ETS](image-url)
The building’s simulation model was realized using DOE-2 software. In order to validate the building model, it was necessary to compare the results obtained using a simulation with energy bills. We found that the global mean difference (these can be more or less important for each month) between annual energy consumption, obtained using the simulation model, and the annual energy bill was only about 2.8%. (Stanescu et al., 2007)

Figure 5 shows all five levels of the building: zone numbers are marked. Approximately 75 zones were used in our optimization method.

a) Optimization using mutation as the only variation operator

Optimization without crossover may be classified as an evolutionary strategy (ES), because it involves a real-valued representation of individuals; mutation is crucial (sometimes it is the only operator), and recombination is secondary (Eiben and Smith 2003, Fong et al. 2006). In our case, the probability of chromosome mutation was approximately 0.9, since the evolution strategy selected used mutation as its primary search mechanism. The probability of gene mutation varied according to the form of mutation operator used, and the random changes applied by the algorithm modified individual genes and improved the value of the fitness function.

b) Optimization using crossover and mutation as variation operators

This type of optimization algorithm respects the principles of a genetic algorithm (GA) and uses crossover and mutation operators as variation operators. In our case, the probability of chromosome mutation was about 0.5 and the probability of chromosome recombination was about 0.4.

c) Optimization using crossover as the only variation operator

In order to see how the EAs perform when there is no mutation, we tested an optimization algorithm using crossover as the only variation operator. In our case, the algorithm selected genes from the individuals in the initial population and recombined them. The probability of chromosome crossover was approximately 0.8, since the evolutionary algorithm uses crossover as the primary search mechanism.

For all types of EA, we used elitism in order to preserve the best solution found: we placed the individual with the best fitness from each tournament selection into the next generation.

DISCUSSION AND ANALYSIS OF RESULTS

We compared the three types of EA presented above, and chose the fast optimization method, which yielded the best optimization results.

### Table 1

<table>
<thead>
<tr>
<th>ITERATIONS</th>
<th>HVAC ENERGY CONSUMPTION, [MWh]</th>
</tr>
</thead>
<tbody>
<tr>
<td>100</td>
<td>2114.1</td>
</tr>
<tr>
<td>250</td>
<td>2073.3</td>
</tr>
<tr>
<td>500</td>
<td>2064.2</td>
</tr>
</tbody>
</table>

Optimization evolution curves are shown in Figure 6, for 500 iterations (or generations). We observed that these optimization curves were comparable for the three cases studied (a, b, or c). A wide gap in computing time remained, however: Case a) required only 2 days to find the optimum solution, while Case b) required 3½ days and Case c) required 4 days. This discrepancy in computing time is a consequence that the three methods diverge in the number of calls to evaluate the objective function.

<table>
<thead>
<tr>
<th>Case</th>
<th>Computing time</th>
</tr>
</thead>
<tbody>
<tr>
<td>a) mutation</td>
<td>2 days</td>
</tr>
<tr>
<td>b) mutation + crossover</td>
<td>3 ½ days</td>
</tr>
<tr>
<td>c) crossover</td>
<td>4 days</td>
</tr>
</tbody>
</table>

Intermediary results for HVAC energy consumption for the three cases studied are also shown in Table 1 for 100, 250 and 500 iterations. The differences in HVAC energy consumption after 500 iterations are quite small. Between Case a) and Case c), we find 0.66% savings (10.85 MWh), and 2.9% savings (64.35 MWh) between Cases b) et c).
Compared optimization results for the reference and existing buildings are shown in Table 2. Here we see that the optimum solutions yielded 6 systems, and we also note a reduction in total AFR of approximately 8%, as compared to the reference building. HVAC energy consumption savings were approximately 25% compared to those for the reference building, and about 20% compared to the existing building. For Table 2 as well as Figure 6, we decided to retain Case a) as the optimum solution for our problem, that is to say, an optimization process using mutation as variation operator. In our view, this represented a good compromise between length of computing time (2 days instead of 3½ or 4 days) and optimization results. We based our choice partly on the fact that we had used the number of iterations, i.e. 500, as our stopping criterion. If we had chosen desired consumption (which had been hard to quantify in the preliminary design) as the stopping criterion, then the optimization would have stopped when the HVAC energy consumption target was reached, thereby using less computation time. It is also true that types of variation operators used in an optimization problem can slightly alter optimization results.

Optimal zone groupings for Solution a) are shown in Table 3. The zones have the same numbering as those shown in Figure 5.

Zones were grouped mainly in order to serve one or two façades of the building and also in order to respect the \( C_{\text{all}} \) constraint. We also noted there were systems that grouped zones located on only two or three levels of the building. Internal and external zones are often grouped under the same system, to provide more load diversity.

For this optimization problem, we did not take into account the constraint related to the practice of grouping zones with different occupancy schedules under a single system. We did find, however, that zone operation schedules were taken into consideration during the optimization process. Compared to the reference or existing building, where each system serves all types of zone schedule, in the optimum solution there were systems serving only one type of zone schedule. On the other hand, the constraints imposed, mainly \( C_{\text{FR}} \), forced zones with different schedules to be grouped under the same system.

**Table 2: Results comparison between the reference, existent and optimized building HVAC system design**

<table>
<thead>
<tr>
<th>SOLUTION</th>
<th>NUMBER OF SYSTEMS</th>
<th>SYSTEM EXTENT, ([m_{\text{extent}}])</th>
<th>FAN ENERGY CONSUMPTION, [MWh]</th>
<th>HVAC ENERGY CONSUMPTION, [MWh]</th>
<th>HVAC ENERGY SAVINGS</th>
<th>TOTAL AFR, [L/s]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reference building</td>
<td>6</td>
<td>2.8075*10^4</td>
<td>688.57</td>
<td>2691</td>
<td>-</td>
<td>115190</td>
</tr>
<tr>
<td>Existing building</td>
<td>4</td>
<td>2.8161*10^4</td>
<td>657.05</td>
<td>2544.9</td>
<td>5.42%</td>
<td>111150</td>
</tr>
<tr>
<td>Solution a)</td>
<td>6</td>
<td>2.6559*10^4</td>
<td>603.84</td>
<td>2064.2</td>
<td>23.29%</td>
<td>105549</td>
</tr>
<tr>
<td>Solution b)</td>
<td>6</td>
<td>2.7628*10^4</td>
<td>595.03</td>
<td>2016.7</td>
<td>25.05%</td>
<td>106153</td>
</tr>
<tr>
<td>Solution c)</td>
<td>6</td>
<td>2.7650*10^4</td>
<td>605.54</td>
<td>2078.1</td>
<td>22.78%</td>
<td>105854</td>
</tr>
</tbody>
</table>

**Table 3: Zone groupings for Optimal Solution a)**

<table>
<thead>
<tr>
<th>SYST.</th>
<th>ZONES</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>1, 4, 22, 23, 26, 27, 28, 34, 37</td>
</tr>
<tr>
<td>S2</td>
<td>3, 19, 21, 31, 32, 33, 36, 39, 41, 44, 46, 47, 56, 68, 71, 73</td>
</tr>
<tr>
<td>S3</td>
<td>10, 12, 29, 35, 49, 51, 61, 69</td>
</tr>
<tr>
<td>S4</td>
<td>8, 16, 24, 40</td>
</tr>
<tr>
<td>S5</td>
<td>2, 5, 6, 7, 11, 13, 15, 20, 25, 30, 38, 42, 43, 45, 48, 50, 52, 53, 54, 55, 57, 58, 59, 60, 62, 63, 64, 65, 66, 67, 70, 72, 74, 75</td>
</tr>
<tr>
<td>S6</td>
<td>9, 14, 17, 18</td>
</tr>
</tbody>
</table>

**CONCLUSION**

This paper has applied the CR_CONS optimization method to a real building; it has demonstrated that the proposed optimization method can be adapted for preliminary HVAC system design. A comparison among three different permutation options (in terms of optimization results, computing time and convergence speed) was done in order to select an optimal solution for our problem. The solutions include an optimal number of HVAC systems as well as an optimal grouping of zones for each building studied. This method therefore contributes to improving HVAC system design, because the solutions generated by this optimization method ensure that all available VAV candidate systems are considered in this process, while respecting the constraints imposed.

Comparing EA using three different permutation options, we determined that an EA using only mutation as variation operator constitutes a good compromise among factors such as optimization results, convergence speed and especially, computing time. It must be specified, however, that this decision depends upon the stopping criterion as well as on the variation operators used in the optimization problem,
which can slightly alter the results. It follows that the evolutionary nature of the search algorithm has a substantial impact in terms of fitness function evaluation count (= computation time) and quality of solution. This type of evolutionary algorithm, using mutation as the only variation operator, was used in our work.

For our optimization problem, HVAC energy consumption savings were 22.7% to 25%, compared to those for the reference building, and about 18.3% to 20.8%, compared to the existing building. In general, these energy savings depended upon building configuration, types of HVAC systems, and their control strategies. Diversity in building load profiles also had a significant impact on energy savings.

REFERENCES


